A Global View of Creative Destruction

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Abstract

U.S. exports exhibit the telltale sign of creative destruction on a global scale: simultaneous expansion and contraction across categories and firms. The exports of exporting firms are considerably more volatile than the domestic sales of the same firms. To mimic these patterns, we formulate a model of creative destruction by both domestic and foreign firms. In the model, trade liberalization (or openness more generally) quickens the pace of creative destruction and facilitates the flow of technology across countries. The resulting dynamic gains from trade and openness are an order of magnitude larger than the static gains in standard trade models.

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1 Introduction

Studies by Bernard and Jensen (1999), Eaton and Kortum (2002), Melitz (2003), and others placed heterogeneous firms at the center of research on international trade. The first wave of follow-up research has focused mostly on models in which trade liberalization leads to a burst of reallocation and growth, but no long run effects on either.


In this paper we present facts and a model on the interaction of creative destruction and trade. We document ample reallocation of U.S. manufacturing exports at the 4-digit level across years. Expanding and contracting categories typically reallocate 13% of all exports (over and above growth in aggregate export) in a given year. At the firm-level, meanwhile, we find that export growth — including entry and exit into exporting — is twice as volatile as domestic sales growth over five-year intervals in the U.S. Census of Manufacturing. Thus exports are associated with elevated reallocation at the firm level, and ample churn at the 4-digit category level.

Motivated by these facts, we specify a model with global creative destruction. In our model, innovating firms draw a Pareto-distributed quality improvement over existing technology. When innovators take over the market for an existing product (creative destruction), export reallocation across countries can take place. Domestic firms can take over foreign markets for a product, and foreign firms can take over the domestic market. This is a two-economy version of the influential Klette and Kortum (2004) model of creative destruction, only with exogenous arrival rates.
In our baseline version of the model, innovators build on the technology of sellers. In this version trade facilitates the flow of ideas across countries. But we also consider versions in which innovators focus on the technology of domestic producers, or in which ideas flow across countries independent of trade as in Ramondo, Rodríguez-Clare and Saborío-Rodríguez (2016). In all versions, our two economies grow at the same long run rate due to the diffusion of ideas.

We calibrate the model to fit manufacturing moments in the U.S. vs. the rest of the OECD. We match TFP growth, relative value added per worker in the U.S. and the OECD, exports relative to all shipments (the trade share), and the sensitivity of trade to trade barriers (the trade elasticity). To pin down the Pareto shape parameter we fit the gap in revenue per worker for exporting vs. non-exporting firms in U.S. manufacturing. We also target value added per worker and employment in the U.S. vs the rest of the OECD. We infer higher innovation rates in the U.S. given its higher GDP per worker.

Once calibrated, we analyze the model transition dynamics and steady state response to tariff changes. In the baseline version of the model, wherein innovators build on sellers, lower tariffs boost the long run growth rate. Even taking into account the transition, the gains from trade relative to autarky are equivalent to a permanent 37% increase in consumption in the U.S., compared to around 1% in a static version of the model. Thus the dynamic growth gains from trade are large in our baseline model. Because the U.S. is more innovative than the rest of the OECD, the rest of the OECD benefits more from trade than the U.S. despite the higher trade share in the U.S.

To dissect our dynamic gains from trade, we entertain alternative assumptions about idea flows across countries. When we assume countries learn partially from local producers rather than sellers into the local market, the gains from trade shrink toward the static gains. If ideas flow independent of trade, then lower tariffs do not affect the long run growth rate at all. Thus idea flows are critical to our large dynamic gains from trade. When we assume countries specialize in innovating on products they produce, the dynamic gains remain
large for the U.S. Given its innovativeness, the U.S. gains a lot from specializing its draws on a subset of products. Due to limited idea flows across countries, the rest of the OECD benefits less from trade when there is research specialization. Models with limited idea flows and research specialization, however, predict much less reallocation of exports across categories than observed in the data.

Our effort is most closely related to three recent papers. Perla, Tonetti and Waugh (2020) study the impact of trade on exit, entry, domestic technology diffusion, and growth in a model of symmetric countries. Like us, they find large dynamic gains from trade. They derive analytical steady state solutions in a model of many countries, whereas we simulate a two-country model calibrated to evidence on trade and job flows. Our focus is innovation, idea flows across countries, and creative destruction, whereas their focus is on the interaction of trade with domestic technology diffusion.

We follow Buera and Oberfield (2020) in studying international technology diffusion in a model with Bertrand competition. They endogenously obtain Frechet distributions of productivity within countries, allowing them to characterize multilateral trade flows as in Bernard, Eaton, Jensen and Kortum (2003). They stress that the dynamic effects of trade could be small or even negative depending on whether firms learn from domestic producers or from sellers into the domestic market. Our focus is more empirical, as we try to match evidence on export reallocation across categories and firms. And we argue that these facts are consistent with knowledge flows across countries.

Akcigit, Ates and Impullitti (2018) are similar to us in characterizing the impact of tariffs on growth in a two-country model with technology spillovers. Theirs is a step-by-step innovation model, with escape-from-competition effects that are crucial for how trade can induce more innovation. They analyze transition dynamics and optimal R&D subsidies. They emphasize the convergence of patenting in other advanced countries toward the U.S. in recent decades. In our model and empirics, in contrast, we focus on how trade affects export reallocation at the category and firm levels.
The rest of the paper is organized as follows. Section 2 presents facts about export reallocation across categories and firms. Section 3 lays out the details of our baseline model. Section 4 describes alternative specifications with more limited knowledge spillovers. We denote Section 5 to calibrating the models and judging their fit. In section 6 we assess the gains from trade (and idea flows more generally) in our model. Section 7 concludes.

2 Facts about U.S. export reallocation

We look at fluctuations in 4-digit exports from the U.S. across years in the World Trade Flows Database maintained by Feenstra, Lipsey, Deng, Ma and Mo (2005). There are 540 4-digit SITC (revision 2) manufacturing industries in the database, and we use years 1982 through 2003. We calculate the aggregate rate of export reallocation across categories in the same way that Davis, Haltiwanger and Schuh (1996) calculate job reallocation rates across firms. We add up the increase in exports in all categories showing an increase in exports from one year to the next, and do the same for all categories showing a decrease in exports. We then divide by the mean of aggregate exports in the adjacent years, and average the export creation rate and the export destruction rate. The averaging nets out aggregate export growth, including from changes in price levels.

Our focus is this “excess” export reallocation across categories above and beyond what would be needed to achieve the average growth rate of exports. We seek to gauge the magnitude of such reallocation because it could be a byproduct of creative destruction on a global scale. That is, a country starts exporting new things at the same time that it ceases exporting other things.¹

For firm-level exports, domestic sales, and employment, we use the U.S. Census of Manufacturing. We analyze the Census years 1987, 1992, ..., 2012 because exports became available in 1987, and 2012 is the latest year to which

¹Our statistics on country-level export reallocation are related to Hanson, Lind and Muendler (2018)’s measure of mean reversion of a country’s top export.
we have access. We obtain domestic sales by subtracting exports from total sales at the firm level.

We calculate the standard deviation across firms of their growth rate of exports and domestic sales, respectively. To take into account firms entering and exiting (either exports or domestic sales), we take the arc growth rate: the change in exports (or domestic sales) divided by the average of current and previous period exports (or domestic sales). This is over five-year periods so that we can see all firms with employees in the Manufacturing Census.

Table 10 lists five moments we glean from the World Trade Database and the U.S. Census of Manufacturing. The excess reallocation of exports across 4-digit categories equals 13% per year. The unweighted exit rate from categories altogether is around 8%. Across firms, export growth is more dispersed than is domestic sales growth, especially if one compares them within exporting firms. The standard deviation is 1.72 for export growth and 1.20 for domestic sales of exporting firms. This is consistent with the notion that exporting exposes a firm to creative destruction from a foreign firm to a greater extent than selling in the domestic market. Both types of sales are subject to creative destruction from other domestic firms.

**Table 1: Export Reallocation Facts**

<table>
<thead>
<tr>
<th>Data Moment</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Country-Level Export Reallocation</strong></td>
<td></td>
</tr>
<tr>
<td>Export Category Creation/Destruction</td>
<td>13.0%</td>
</tr>
<tr>
<td>Category Exit Rate</td>
<td>7.8%</td>
</tr>
<tr>
<td><strong>Firm Level Sales Volatility</strong></td>
<td></td>
</tr>
<tr>
<td>SD of Export Growth</td>
<td>1.72</td>
</tr>
<tr>
<td>SD of Domestic Sales Growth for Exporting Firms</td>
<td>1.20</td>
</tr>
<tr>
<td>SD of Domestic Sales Growth for All Firms</td>
<td>1.50</td>
</tr>
</tbody>
</table>
Table 2: Job Flows in the U.S.

<table>
<thead>
<tr>
<th>Data Moment</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job Creation Rate</td>
<td>31.4%</td>
</tr>
<tr>
<td>Job Destruction Rate</td>
<td>36.6%</td>
</tr>
<tr>
<td>Job Destruction from Large Firms</td>
<td>30.7%</td>
</tr>
</tbody>
</table>

Note: Job creation and destruction rate are calculated over successive five year periods from 1987 to 2012 for the U.S. and from 1973 to 2012 for Canada. Jobs from exports are imputed as the product of firm employment and the ratio of exports to total shipments. “Large” refers to above-mean employment in the initial year of each five year period.

As our model will revolve around creative destruction, it will be important to see if the model generates realistic amount of overall job creation and destruction across firms. Table 2 presents manufacturing job creation and destruction rates over five year periods in the in the U.S. from 1987 to 2012.\(^2\) As in the classic work by Davis, Haltiwanger and Schuh (1996), job flows are large. The average job creation and destruction rate over five years is over 30% in the U.S. Table 2 also presents the job destruction rate among firms with above-average employment in the initial period. Such large firms account for 84% of all job destruction in U.S. manufacturing.

We now look at differences in the size and labor productivity of exporting and non-exporting firms. Figure 1 plots the distribution of employment (in the left panel) and labor productivity (revenue per worker, in the right panel) from the U.S. manufacturing census in 2012. This figure reveals that labor produc-

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\(^2\)The job creation rate between year \(t\) and \(t + 5\) is defined as the ratio of (a) the sum of employment of new firms established between year \(t\) and year \(t + 5\) and the change in employment among expanding firms between the two years; to (b) average total employment across years \(t\) and \(t + 5\). The job destruction rate between years \(t\) and \(t + 5\) is the sum of employment in year \(t\) of firms that exited between the two years and the change in employment between years \(t\) and \(t + 5\) among contracting firms divided by average total employment (in the beginning and ending years). Job flows for the U.S. are calculated for every five year period from 1987 to 2012.
Figure 1: Distribution of Employment and Labor Productivity

Note: The distribution of labor productivity (value-added per worker) and employment of exporting and non-exporting firms in the 2012 U.S. Census of Manufacturing.

Activity and employment is higher for exporters than for non-exporters, and there is overlap of labor productivity and employment between exporters and non-exporters.

The only moment we have discussed so far that we target in our model calibration is the 6.6% gap in revenue per worker between exporting and non-exporting firms. Table 3 displays the other six data moments we target. In steady state we fit TFP growth of 3% per year, manufacturing output per worker in the home country (the U.S.) that is 29% higher than in the foreign country (the rest of the OECD), and a roughly 14% employment share of entering firms over five-year periods. We also target a trade share of 10% in the U.S. and the relative size manufacturing employment in the U.S. compared to the rest of the OECD of 39%. In the World Trade Database, there is a factor of 20 difference in exports between the 75th and 25th percentile SITC’s. Finally, we target the trade elasticity of around 5 in Head and Mayer (2014)’s review article.
Table 3: Data Moments used for Calibration

<table>
<thead>
<tr>
<th>Data Moment</th>
<th>Source</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue per worker exp./non-exp.</td>
<td>U.S. mfg</td>
<td>1.066</td>
</tr>
<tr>
<td>TFP growth rate</td>
<td>U.S. mfg</td>
<td>3.01%</td>
</tr>
<tr>
<td>Value added per worker home/foreign</td>
<td>U.S. and OECD mfg</td>
<td>1.29</td>
</tr>
<tr>
<td>Employment share of entrants</td>
<td>U.S. mfg</td>
<td>14.4%</td>
</tr>
<tr>
<td>Export share of revenues (home)</td>
<td>U.S. mfg</td>
<td>10.2%</td>
</tr>
<tr>
<td>Employment home/foreign</td>
<td>U.S. and OECD mfg</td>
<td>0.389</td>
</tr>
<tr>
<td>Exports in 75th/25th SITC</td>
<td>World Trade Database</td>
<td>20</td>
</tr>
<tr>
<td>Trade elasticity</td>
<td>Head and Mayer (2014)</td>
<td>−5</td>
</tr>
</tbody>
</table>
3 Baseline Model

This section presents a model of growth driven by creative destruction, where innovation can come from domestic or foreign firms.

3.1 Static Equilibrium

The static part of our model is similar to Bernard et al. (2003), or to Dornbusch, Fischer and Samuelson (1977) only with markup heterogeneity.

Utility of the home-country representative consumer is given by consumption of a continuum of varieties \( C_j \) with measure 1:

\[
U = \int_0^1 \ln C_j \, dj.
\] (1)

This utility function implies that consumers spend the same on each variety.\(^3\)

Output of each variety is the product of labor and the quality of the blueprint for the product. We denote \( A_j \) as the “best” blueprint for \( j \) among domestic firms. \( A^*_j \) is the corresponding best blueprint for \( j \) among foreign firms. If we order products so that the index \( j \) is decreasing in \( A_j / A^*_j \), then products \( j \in [0, x] \) are traded and produced at home, \( j \in [x, x^*] \) are non-traded, and \( j \in [x^*, 1] \) are traded and produced abroad. The cutoff products \( x \) and \( x^* \) are defined by

\[
\frac{A_x}{\tau} = \omega A^*_x
\] (2)

\[
A_{x^*} = \frac{\omega A^*_x}{\tau}
\] (3)

where \( \omega \) denotes the relative wage (domestic relative to foreign) and \( \tau \geq 1 \) is the symmetric gross trade cost. When \( \tau = 1, x = x^* \) and all products are traded.

The owner of the best blueprint sets their quality-adjusted price to push their closest competitor out of the market (Bertrand competition), so the gross

\[^3\text{Utility of the foreign consumer is analogously given by } U^* = \int_0^1 \ln C^*_j \, dj.\]
Table 4: Markups

<table>
<thead>
<tr>
<th>Traded Produced in Home</th>
<th>Non-Traded</th>
<th>Traded Produced in Foreign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>$A_j$</td>
<td>$A_j/\tau$ max $\frac{A_j'}{\tau}, \omega A_j^*$</td>
</tr>
<tr>
<td>Foreign</td>
<td>$A_j/\tau$ max $\frac{A_j'}{\tau}, \omega A_j^*$</td>
<td>$A_j^<em>$ max $\frac{A_j'}{\tau}, \omega A_j^</em>$</td>
</tr>
</tbody>
</table>

markup is the gap between the incumbent firm’s marginal cost and the cost of its closest competitor — domestic or foreign. Table 4 summarizes the markups: $\mu_j$ for domestic firms and $\mu_j^*$ for foreign firms. $A_j'$ and $A_j''$ denote the productivity of the second best producer in the domestic and foreign markets, respectively. These potential competitors do not produce in equilibrium but affect markups.

The relative wage is pinned down by balanced trade:

$$ I^* \cdot x = I \cdot (1 - x^*) $$

where $I$ and $I^*$ denote nominal GDP at home and abroad, respectively. The left hand side of equation (4) is the home country’s exports and the right hand side is the home country’s imports. Nominal GDP in each country is given by

$$ I = \frac{\overline{\mu} w L}{1 - \frac{1 - \tau}{\tau} \cdot (1 - x^*)} \quad \text{and} \quad I^* = \frac{\overline{\mu}^* w^* L^*}{1 - \frac{1 - \tau}{\tau} \cdot x^*} $$

where $\overline{\mu}^*$ and $\overline{\mu}$ denote the average gross markup of foreign and domestic firms, $w$ and $w^*$ are the home and foreign wage, and $L$ and $L^*$ are labor supply at home and abroad.\(^4\) More exactly, the average price-cost markup in the U.S. satisfies

\(^4\)The expression for nominal income comes from equating nominal income to the revenue of local firms plus tariff revenue: $I = \overline{\mu} w L + (\tau - 1) \frac{1}{\tau} (1 - x^*)$ and $I^* = \overline{\mu}^* w^* L^* + (\tau - 1) \frac{1}{\tau} \cdot x^*$. 


\[
\frac{1}{\bar{\mu}} \equiv \frac{\int_{0}^{x^*} \frac{1}{\mu_j} dj + \frac{1}{\tau} \cdot \int_{0}^{x} \frac{1}{\mu^*_j} dj}{x^* + x/\tau}
\]

where \(\mu^*_j\) denotes the markup of domestic firms on their exported products. The expression for the foreign firms’ average markup is analogous.

We can express the real (consumption) wage as a function of the distribution of the best blueprints, markups, the cutoffs, the relative wage, and the trade cost. The real wage at home \(W\) and in the foreign country \(W^*\) are given by

\[
\ln W = \int_{0}^{x^*} \ln \left( \frac{A_j}{\mu_j} \right) dj + \int_{x^*}^{1} \ln \left( \frac{A^*_j}{\mu^*_j} \cdot \frac{\omega}{\tau} \right) dj
\]

\[
\ln W^* = \int_{0}^{x} \ln \left( \frac{A_j}{\mu_j} \cdot \frac{1}{\omega \tau} \right) dj + \int_{x}^{1} \ln \left( \frac{A^*_j}{\mu^*_j} \right) dj.
\]

The home country buys \(j \in [x^*, 1]\) from the foreign country, so the domestic real wage is increasing in the productivity of foreign firms on these products. Likewise, the foreign country purchases \(j \in [0, x]\) from the home country so the foreign real wage increases with domestic firm productivity on these products.

### 3.2 Innovation

We now introduce dynamics to the model. As in Klette and Kortum (2004), a firm is a portfolio of products, an entrant has one product while incumbent firms potentially produce many varieties, and innovation only takes the form of creative destruction. Unlike Klette and Kortum, we allow trade and for creative destruction to come from a firm in another country.

We posit constant exogenous arrival rates for innovation.\(^5\) Arrivals are proportional to the number of products owned by a firm; a firm with two products is twice as likely to creatively destroy another firm’s variety compared to a firm with one product. We assume that innovation builds on the quality of the prod-

\(^5\)In an earlier version of the paper we endogenized arrival rates as a function of research labor. The model’s steady state properties are very similar. See Hsieh, Klenow and Nath (2019).
uct sold in the innovating firm’s *local* market. Later we will entertain alternative assumptions, such as learning from domestic producers only.

The quality of an innovation follows a Pareto distribution with shape parameter $\theta$ and scale parameter equal to the existing quality level. The average percent improvement in quality over an existing variety (conditional on innovation) is thus $\frac{1}{\theta - 1} > 0$. We add a “reflecting barrier” whereby the bottom $\psi$ percent of products in each year, in terms of their quality, redraw their quality from the top $1 - \psi$ percent of domestically produced products. This is in the spirit of what Perla et al. (2020) obtain endogenously, and will help maintain a stationary distribution of quality across products, when scaled by the growing mean quality in response to innovation.

The notation for innovation probabilities is given in Table 5. The probability a product is improved upon by an incumbent domestic firm is $\lambda$. Conditional on not being improved by a domestic incumbent, $\eta$ is the probability the product is improved by an entering domestic firm. Conditional on not being improved by *any* domestic firm, $\lambda^*$ is the probability the product will be improved by a foreign incumbent firm. Finally, conditional on the product not being improved upon by either a domestic firm or by a foreign incumbent, $\eta^*$ is the probability a foreign entrant innovates on the best blueprint. In short, a given product can be improved upon by a domestic incumbent firm, a domestic entrant, a foreign incumbent firm, or a foreign entrant.

Table 6 gives the probability of creative destruction in domestic (rows 1-3) and foreign markets (rows 4-6) due to innovation by domestic (column 1) and foreign firms (column 2). The first row shows the arrival rate of ideas in the domestic market for an exported product. The probability such a product is

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7The *unconditional* probabilities of each type of innovation are $\lambda, \tilde{\eta} \equiv \eta(1 - \lambda)$, $\tilde{\lambda} \equiv \lambda^*(1 - \lambda)(1 - \tilde{\eta})$, and $\tilde{\eta}^* \equiv \eta^*(1 - \lambda)(1 - \tilde{\eta})(1 - \tilde{\lambda}^*)$. So the unconditional probability a domestic firm (entrant or incumbent) improves a product is given by $\lambda + \tilde{\eta}$, and the unconditional probability a foreign firm innovates is $\lambda^* + \tilde{\eta}^*$. 

Table 5: Channels of Innovation

<table>
<thead>
<tr>
<th></th>
<th>Domestic Firm</th>
<th>Foreign Firm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation by incumbents</td>
<td>$\lambda$</td>
<td>$\lambda^*$</td>
</tr>
<tr>
<td>Innovation by entrants</td>
<td>$\eta$</td>
<td>$\eta^*$</td>
</tr>
</tbody>
</table>

Note: The average improvement in quality is $\frac{1}{\theta-1}$.

improved upon by another domestic firm is $\lambda + \tilde{\eta}$, and a domestic innovator will always replace the incumbent firm in this market. A foreign firm improves upon the same product with probability $\tilde{\lambda}^* + \tilde{\eta}^*$, but will not necessarily replace the domestic incumbent. Since quality improvement follows a Pareto distribution, the probability that the quality improvement of the foreign innovator is large enough to replace the domestic incumbent is $\min \left[ \left( \frac{\omega}{\tau} \right)^\theta, 1 \right]$.

For a given innovation rate by foreign firms, higher relative wages $\omega$ and lower trade costs $\tau$ increase the probability that innovation by a foreign firm benefits domestic consumers. Intuitively, higher domestic wages increase the probability a foreign innovator will be competitive enough to replace the incumbent in the domestic market. Higher trade costs make the foreign innovator less competitive compared to the domestic incumbent. Effectively, trade costs insulate domestic firms from foreign competition in the domestic market.

The expected growth rate of the real consumption wage in the domestic market is the product of the rate of creative destruction in rows 1-3 in Table 6 and the increases in product quality (conditional on the product being replaced). And the expected growth rate of the foreign real consumption wage is the product of the arrival rates in rows 4-6 in Table 6 and the corresponding improvements in quality. Real growth rates in the two countries depend on the arrival rates of innovation $\lambda + \tilde{\eta}$ and $\tilde{\lambda}^* + \tilde{\eta}^*$, the relative wage $\omega$, and the share of each type of product ($x$ and $x^*$). As discussed in the previous section, the relative wage and the share of products made by each country are pinned down by balanced trade
Table 6: Probability of Creative Destruction

<table>
<thead>
<tr>
<th>Market</th>
<th>Product Type</th>
<th>Domestic Firm</th>
<th>Foreign Firm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>Exported by Home</td>
<td>$\lambda + \tilde{\eta}$</td>
<td>$(\tilde{\lambda}^* + \tilde{\eta}^*) \min \left( (\omega)\theta, 1 \right)$</td>
</tr>
<tr>
<td></td>
<td>Non-Traded</td>
<td>$\lambda + \tilde{\eta}$</td>
<td>$(\tilde{\lambda}^* + \tilde{\eta}^<em>) \min \left( \left( \frac{\omega A^</em>_j}{\omega A^*_j} \right) \theta, 1 \right)$</td>
</tr>
<tr>
<td></td>
<td>Imported by Home</td>
<td>$(\lambda + \tilde{\eta}) \min \left( \left( \frac{\omega}{\tau A^*_j} \right)\theta, 1 \right)$</td>
<td>$\tilde{\lambda}^* + \tilde{\eta}^*$</td>
</tr>
<tr>
<td>Foreign</td>
<td>Exported by Home</td>
<td>$\lambda + \tilde{\eta}$</td>
<td>$(\tilde{\lambda}^* + \tilde{\eta}^*) \cdot \min \left( (\omega\tau)\theta, 1 \right)$</td>
</tr>
<tr>
<td></td>
<td>Non-Traded</td>
<td>$(\lambda + \tilde{\eta}) \min \left( \left( \frac{A^<em>_j}{\omega A^</em>_j} \right)\theta, 1 \right)$</td>
<td>$\tilde{\lambda}^* + \tilde{\eta}^*$</td>
</tr>
<tr>
<td></td>
<td>Imported by Home</td>
<td>$(\lambda + \tilde{\eta}) \min \left( \left( \frac{1}{\omega\tau} \right)\theta, 1 \right)$</td>
<td>$\tilde{\lambda}^* + \tilde{\eta}^*$</td>
</tr>
</tbody>
</table>

and the distribution of relative technologies $A^*_j/A^*_j$. The distribution of $A^*_j/A^*_j$ is endogenous to innovation.

To illustrate how quality advances because each country builds on the innovations of the other country, it is useful to consider the case of completely free trade ($\tau = 1$). In this case, all products are traded so the relevant arrival rates in Table 6 are rows 1 and 3 (for the domestic market) and rows 4 and 6 (for the foreign market). The probability a domestic firm creatively destroys another firm is thus given by:

**Domestic creative destruction rate**

$$\text{Domestic creative destruction rate} = (\lambda + \tilde{\eta}) \cdot x^* + (\lambda + \tilde{\eta}) \min \left[ \omega^{-\theta}, 1 \right] \cdot (1 - x^*).$$

The first term is the probability a domestic firm replaces a product made by another domestic firm and the second term is the probability a domestic firm replaces a variety produced by a foreign firm. The corresponding rate of creative destruction by a foreign firm under free trade ($\tau = 1$) is:

**Foreign creative destruction rate**

$$\text{Foreign creative destruction rate} = (\tilde{\lambda}^* + \tilde{\eta}^*) \cdot (1 - x^*) + (\tilde{\lambda}^* + \tilde{\eta}^*) \min \left[ \omega^\theta, 1 \right] \cdot x^*.$$
Ceteris paribus, higher $\omega$ lowers the rate of creative destruction of domestic firms and raises that of foreign firms. In steady state, the equilibrium relative wage equates the rate of creative destruction by domestic firms to that of foreign firms. So, if domestic firms are more innovative, domestic wages are higher but creative destruction rate of domestic firms is the same as that of foreign firms.

It is also helpful to contrast autarky and free trade when the two countries are symmetric in size and in their innovation arrival rates. In this special case the relative wage $\omega = 1$ and the expressions become simply:

\[
\text{Autarky growth rate} = (\lambda + \tilde{\eta}) \frac{1}{\theta - 1}.
\]
\[
\text{Frictionless growth rate} = \left(\lambda + \tilde{\eta} + \tilde{\lambda}^* + \tilde{\eta}^*\right) \frac{1}{\theta - 1}.
\]

In autarky each country benefits only from domestic arrivals. With frictionless trade, each country benefits from both domestic and foreign arrivals. This underscores the scale effect generating dynamic gains from trade in this model.\(^8\)

### 3.3 Numerical steady state comparative statics

We now illustrate the model's behavior in response to changes in trade costs (tariffs) and foreign arrival rates. We will discuss the calibration in detail in a later section, after documenting facts about export reallocation. Because we will calibrate the home and foreign markets to the U.S. and the rest of the OECD, we refer to them here as simply U.S. and OECD. Our emphasis in this subsection is qualitative properties rather than magnitudes.

Figure 2 shows that rising trade costs lower the common long run growth rate of the two economies. When fewer goods are traded, countries are less frequently building on each other's innovations and more frequently building only on their own innovations. As the U.S. is the richer and therefore the more

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\(^8\)Section A.3 of the online Appendix shows the expected growth rate for the general case with trade frictions and assymmetric innovation rates.
innovative country (from the model’s perspective), higher trade costs raise the U.S. wage relative to the OECD wage. That is, the OECD suffers more from building less on U.S. innovations than the other way around.

Figure 2: Growth and Relative Wage Trade Cost Counterfactuals

Figure 3 shows that higher trade costs lower the trade share, as one would expect. Less obviously, the Figure reveals that the trade elasticity also falls with trade costs. We display the effect of a higher arrival rate of innovations in the OECD in Figure 4. A higher innovation rate raises the common growth of TFP in the two economies, but also lowers the wage in the U.S. relative to the OECD.

Figure 3: Trade Share and Trade Elasticity Trade Cost Counterfactuals
Figure 4: Growth and Relative Wage Foreign Innovation Counterfactuals

Figure 5 shows that the trade share declines as the OECD innovation rate rises. A higher OECD innovation rate moves the relative wage down closer to 1, so that OECD innovators do not take over as many U.S. exported products. Comparing Figures 4 and 5, a higher arrival rate in the OECD causes the growth rate and trade to move in the opposite direction. This indicates that, even in a model in which lower trade costs boost trade and growth, the relationship between trade and growth is not monotonic.

Figure 5 also demonstrates that the trade elasticity rises with the OECD arrival rate. When the OECD builds more frequently on U.S. exported products, it tethers the quality of products produced in the OECD more closely to those in the U.S. When comparative advantage is weaker, there is less trade.

Figure 6 drives home how tariffs and OECD innovation rates, respectively, affect the dispersion of relative quality in the U.S. vs. OECD. The left panel shows that lower trade costs narrows the dispersion relative quality, as ideas flow more quickly across countries with more trade. The right panel reveals that a higher OECD innovation rate narrows the distribution of relative qualities. The fact that the OECD is less innovative than the U.S. is critical for this result.

In our baseline model, innovators build on the quality of sellers into the local market. Suppose instead that spillovers target the best foreign products (relative
to domestic quality) regardless of whether they are traded. Specifically, say the OECD draws with probability $z$ on a random U.S. product among the $z$ highest quality products in the U.S. relative to the OECD, and with probability $1 - z$ on domestically produced products. And the U.S. draws with probability $z^*$ on the highest quality OECD products relative to the U.S. We call this the “disembodied spillover” model since the knowledge spillovers are not embodied in trade. This disembodied model is equivalent to our baseline model if the steady state features $z = x$ and $z^* = x^*$, where $x$ and $x^*$ are the fraction of products exported
by the U.S. and OECD, respectively. If \( z \) and \( z^* \) are fixed, however, then the comparative statics with respect to tariffs will differ. Figure 7 shows that TFP growth is no longer decreasing in tariffs. This is because higher tariffs do not impede knowledge flows. The relative wage of the U.S. still rises with tariffs, but much more modestly. The trade share and trade elasticity still fall with tariffs.

**Figure 7: Disembodied Spillovers and Trade Cost Counterfactuals**

Figure 8 shows what happens when we raise the U.S. threshold \( z \) for the products that OECD innovators build on. The growth rate rises, as ideas flow more quickly across countries with a higher \( z \). The U.S. relative wage falls because the OECD benefits disproportionately (we held \( z^* \) fixed here). The trade share falls with higher \( z \) as the OECD qualities hug the U.S. ones more closely, and in turn the trade elasticity rises since comparative advantage is weaker.

### 4 Models with Limited Idea Flows

Our baseline model made two key assumptions about the generation of new ideas. First, we assume innovators build on the productivity level of sellers into the domestic market. Second, we assume innovators attempt to build on the productivity of all products sold in the domestic market. We now consider two alternative assumptions about how new ideas are generated.
Our first alternative assumes that innovators build on sellers with probability $\kappa$ and on domestic producers with probability $1 - \kappa$. If a product is imported, innovators build on the quality of the last domestic producer. Our baseline model is $\kappa = 1$. We will consider a low value of $\kappa = 1$ to contrast with our baseline model. We cannot handle the other extreme of building only on domestic producers $\kappa = 0$ because in that case country growth rates diverge because of their differing arrival rates.

Our second alternative assumes that innovators build on all products with probability $\nu$ and on the subset of products that are domestically produced with probability $1 - \nu$. Such research specialization ($\nu < 1$) allows countries to experience more frequent innovations on the subset of products they produce, and more so the higher the share of products imported. Our baseline case is $\nu = 1$. We will consider $\nu = 0.1$ as a contrasting case with research specialization. Again, we cannot handle the polar extreme of $\nu = 0$ because in that case the two countries will have different long run growth rates.

In Table 7 we compare the properties of our baseline model to those of these two alternative models. In this exercise we hold fixed all parameters except $\kappa$ and $\nu$. Table 7 shows that the baseline model yields more export category reallocation than when innovators build mostly on domestic quality and, especially,
Table 7: Alternative Model Implications for Export Reallocation

<table>
<thead>
<tr>
<th></th>
<th>$\kappa = 1$</th>
<th>$\kappa = 0.1$</th>
<th>$\kappa = 0.1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\nu = 1$</td>
<td>$\nu = 1$</td>
<td>$\nu = 0.1$</td>
<td></td>
</tr>
<tr>
<td>Country-Level Export Reallocation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Export Category Creation/Destruction</td>
<td>12.8%</td>
<td>5.4%</td>
<td>0.6%</td>
</tr>
<tr>
<td>Category Exit Rate</td>
<td>2.9%</td>
<td>0.6%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Firm Level Sales Volatility</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD Export Sales Growth</td>
<td>1.78</td>
<td>1.54</td>
<td>1.66</td>
</tr>
<tr>
<td>SD Domestic Sales Growth for Exporting Firms</td>
<td>1.08</td>
<td>1.23</td>
<td>1.66</td>
</tr>
<tr>
<td>SD Domestic Sales Growth for All Firms</td>
<td>1.42</td>
<td>1.44</td>
<td>1.66</td>
</tr>
</tbody>
</table>

Notes: Parameters are held fixed across the models other than the spillover parameters $\kappa$ (the share of innovation building on sellers) and $\nu$ (the share of innovation building on products a country produces).

when innovation focuses on products that a country currently produces. In the latter case, specializing innovations to what a country is already good at reinforces comparative advantage and leads to minimal export category turnover.

Table 7 also shows that, in the baseline model, firm-level export sales growth is much more dispersed than domestic sales growth. This is notably less true when innovators build on domestic quality levels. And it is not at all true when countries specialize their arrivals on the products they already produce. Our intuition here is confirmed: building on sellers means that exported products are more vulnerable to creative destruction by foreign firms.
5 Calibration and Fit

Our baseline model involves 8 parameters: the shape parameter $\theta$ of the Pareto distribution of the innovation draws; two innovation rates (for incumbents $\lambda$ and entrants $\eta$); the trade cost $\tau$; the rate at which the number of products in a category rises when we rank categories from low to high total exports $\epsilon$; and the fraction of low quality products that redraw from the remainder of the domestic quality distribution each year $\psi$. In this section, we infer the value of these 8 parameters from the 8 moments in the data we laid out in Table 3.

As mentioned, the U.S. is “home” and the rest of the OECD is “foreign”. We back out $\theta$ from the gap in labor productivity (revenue per worker) between exporters and non-exporters. The higher is $\theta$, the smaller the variance in the innovation step size and the smaller the gap between exporter and non-exporter markups. For a given $\theta$ and relative employment $L/L^*$, the innovation arrival rates and the trade cost ($\tau$) jointly determine the growth rate, the trade share, and the relative wage. We use the employment share of new firms to pin down innovation by entrants vs. incumbents. As we will be interested in comparing the model to the data in terms of export reallocation across categories, we need to take a stand on how many products are in each category. We start with 1 product in the smallest category and have the number of products rise at the exponential rate $\epsilon$. Finally, we use the trade elasticity to back out the reflecting barrier $\psi$ and the implied dispersion of product qualities.

We simulate the model with 41,911 varieties in each country. Each variety receives innovation draws that are randomly assigned to an existing incumbent or a new entrant. The relative wage is selected to balance trade between the two countries in each year. We simulate for several hundred years until the economy

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9 Strictly speaking, there is one more parameter, namely the relative employment of home vs. foreign country, which we set directly to match the data. And we do not separately identify the arrival rate of innovations by foreign entrants vs. incumbents, but rather assume this breaks down in the same way the U.S. ratio breaks down.

10 The implied total number of products with our exponential procedure is 41,911 across 650 categories with rounding; there are 650 categories with U.S. exports in at least one year from 1983-2002.
Table 8: Estimates of Model Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>Shape parameter of innovation draws</td>
<td>10.8</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Home innovation rate from incumbents</td>
<td>13.5%</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Home innovation rate from entrants</td>
<td>2.61%</td>
</tr>
<tr>
<td>$\lambda^* + \eta^*$</td>
<td>Foreign innovation rate from incumbents + entrants</td>
<td>12.3%</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Tariff</td>
<td>1.50</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Exponential rate at which # of varieties rise across categories</td>
<td>0.915%</td>
</tr>
<tr>
<td>$\psi$</td>
<td>Reflecting barrier for product quality</td>
<td>1.02%</td>
</tr>
</tbody>
</table>

Note: The arrival rates of innovation are unconditional.

settles down to a steady-state, at which point we calculate moments. We utilize a simulated annealing procedure to search for the parameter values that allow us to match the moments in the data. For more details on our calibration see Section A.2 of our Online Appendix.

The resulting calibrated parameter values are shown in Table 8. The innovation rates in Table 8 are conditional. The unconditional innovation rates are $\lambda + \bar{\eta} = 0.160$ for domestic firms and $\bar{\lambda}^* + \bar{\eta}^* = 0.122$ for foreign firms. The innovation rate has to be higher for domestic firms to explain the 29% higher real wage in the home country. Conditional on the innovation rates and the relative size of the two economies, the trade share pins down the trade cost, a 50% tariff\footnote{Eaton and Kortum (2002) and others infer high trade costs to explain bilateral trade flows.}. We estimate an $\epsilon$ of 0.915% so that exports in the 75th percentile category are 20 times larger than exports in the 25th percentile category, as in the World Trade Database. Finally a reflecting barrier where the bottom 1.1% of products by quality redraw from the top 98.9% of products generates a trade elasticity of 5. A higher $\psi$ narrows the quality distribution and weakens comparative advantage, thereby raising the trade elasticity.
Table 9: Best Fit of Targeted Moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>Target</th>
<th>Baseline</th>
<th>Limited Spillover</th>
<th>Research Specialization</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP Growth</td>
<td>3.0%</td>
<td>3.0%</td>
<td>3.0%</td>
<td>3.0%</td>
</tr>
<tr>
<td>U.S.-OECD Relative Wage Gap</td>
<td>29.0%</td>
<td>29.0%</td>
<td>29.0%</td>
<td>29.0%</td>
</tr>
<tr>
<td>U.S. Export Share of Revenues</td>
<td>10.2%</td>
<td>10.2%</td>
<td>10.2%</td>
<td>10.2%</td>
</tr>
<tr>
<td>Employment Share of Entrants</td>
<td>14.4%</td>
<td>14.4%</td>
<td>14.4%</td>
<td>14.4%</td>
</tr>
<tr>
<td>Trade Elasticity</td>
<td>5.0</td>
<td>5.0</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>log(Revenue/Worker) Exporters vs. Non-Exporters</td>
<td>6.6%</td>
<td>6.6%</td>
<td>1.0%</td>
<td>-0.6%</td>
</tr>
</tbody>
</table>

Table 9 provides information on the fit of the baseline model as well as the two alternative models we described in Section 4. All of the models fit the 3% aggregate TFP growth target, the U.S./OECD wage gap of 29%, the 10.2% U.S. export share, and the 14.4% employment share of entering firms. And the baseline model has no problem fitting the the trade elasticity or the gap in revenue per worker between exporters and non-exporters. But the limited spillover (learning mostly from domestic quality levels) and the research specialization models cannot generate realistic trade elasticities or exporter premiums. With limited spillovers, country quality levels spread out so much across products that comparative advantage is strong and the trade elasticity becomes small.\footnote{\textsuperscript{12}}

In Table 10 we report how the models do in matching untargeted facts about export reallocation. The baseline model comes close to generating a realistic category reallocation rate (12.8% in the model vs. 13% in the data). The reallocation rates are markedly lower for the limited spillover models than in the data, as they feature less global creative destruction. All the models undershoot in terms of the fraction of categories that go from positive exports to no exports.\footnote{\textsuperscript{12}To fit the observed trade share these models with limited spillovers need a higher trade cost than the baseline model.}
The baseline model is not far from the data in terms of the cross-firm standard deviation of export growth and domestic sales growth. The limited spillover models exhibit less elevated dispersion for export growth relative to domestic sales growth. The contrast is not as stark here with parameters re-estimated as in Table 7, wherein parameters were held fixed.

Table 10: Alternative Model Implications (Re-estimated Parameters)

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>$\kappa = 1$</th>
<th>$\kappa = 0.1$</th>
<th>$\kappa = 0.1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country-Level Export Product Reallocation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Export Category Creation/Destruction</td>
<td></td>
<td>13.0%</td>
<td>12.8%</td>
<td>6.2%</td>
</tr>
<tr>
<td>Category Exit Rate</td>
<td></td>
<td>7.8%</td>
<td>2.9%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Firm Level Sales Volatility</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD Export Growth</td>
<td></td>
<td>1.72</td>
<td>1.78</td>
<td>1.67</td>
</tr>
<tr>
<td>SD Domestic Sales Growth for Exporting Firms</td>
<td></td>
<td>1.20</td>
<td>1.08</td>
<td>1.12</td>
</tr>
<tr>
<td>SD Domestic Sales Growth for All Firms</td>
<td></td>
<td>1.50</td>
<td>1.42</td>
<td>1.44</td>
</tr>
</tbody>
</table>

Notes: The arrival rates and trade costs re-estimated across the models, whereas $\theta$ and $\psi$ are held fixed across models.

Table 11 shows that all the models do surprisingly well in matching the overall job creation and destruction rates in the economy, despite these moments not being targeted in the calibration. All the models understate the share of job destruction associated with larger firms.

Figures 9 and 10 show that the baseline model generates overlap in the distribution of employment and labor productivity between exporters and non-exporters, as seen in the data.
Table 11: Other Untargeted Moments

<table>
<thead>
<tr>
<th></th>
<th>κ = 1</th>
<th>κ = 0.1</th>
<th>κ = 0.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>ν = 1</td>
<td>ν = 1</td>
<td>ν = 0.1</td>
</tr>
<tr>
<td>Job Creation Rate</td>
<td>31.4%</td>
<td>31.6%</td>
<td>31.1%</td>
</tr>
<tr>
<td>Job Destruction Rate</td>
<td>36.6%</td>
<td>38.2%</td>
<td>37.7%</td>
</tr>
<tr>
<td>Job Destruction from Large Firms</td>
<td>30.7%</td>
<td>22.3%</td>
<td>20.5%</td>
</tr>
</tbody>
</table>

Note: The U.S. data is the average from 1987 to 2012. The second column shows simulated steady state moments in the model with the parameter values from Table 8.

Figure 9: Distribution of Employment, Data vs. Simulation

Note: The distribution of labor productivity (value-added per worker) and employment of exporting and non-exporting firms in the 2012 U.S. Census of Manufacturing.
Figure 10: Distribution of Revenue per Worker, Data vs. Simulation

Note: The distribution of labor productivity (value-added per worker) and employment of exporting and non-exporting firms in the 2012 U.S. Census of Manufacturing.
6 Gains from Trade

Table 12 (columns 1 and 2) displays the welfare gains from reduction in the gross tariff rate from 1.5 to 1.25 in the baseline model. The gains are in permanent consumption-equivalent terms, which is equivalent to percentage gains in the present discounted value of consumption given our specification of linear utility. For comparison, we start with the static gains implied by the formula in Arkolakis, Costinot and Rodriguez-Clare (2012). The static gains are higher in our model than in the ACR formula, but the discrepancy is modest for the U.S. (3.0% ACR vs. 4.2% for us).

The final two rows of Table 12 present the growth and dynamic gains from trade liberalization. This trade liberalization raises the long run growth rate by 17 basis points from 3% to 3.17% in both the U.S. and OECD. The resulting welfare gain is more than three times as large as the ACR gains at 9.6% in the U.S. The rest of the OECD gains even more (15.5%) because it gets more ideas than it gives.

The gap between the static gains implied by the ACR formula and our calculations are much larger when we consider more dramatic changes in trade costs. In columns 3 and 4 in Table 12 we present the welfare gains from trade when the steady state trade share goes from 0.4% near autarky ($\tau = 4$) to 10.2% in our baseline (with $\tau = 1.50$). The ACR formula predicts a welfare gain of 1.1% for the U.S. As the Table shows, the static gains in our model are much larger than what the ACR formula implies: over 13% for the U.S.

Clearly, our model does not fall into the ACR class. In our model, trade facilitates the flow of ideas across countries. Product quality, and the comparative advantage gains from trade, varies with trade costs. Figure 6 plotted the distribution of relative quality across products for the U.S. versus the rest

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13 By dynamic gains we mean those in the dynamic model. These include both the static gains and the growth gains.

14 The ACR formula for the welfare gains relative to autarky is \((1 - \text{trade share}) - 1/(\text{trade elasticity})\). We use a trade elasticity of 5 based on the survey by Head and Mayer (2014).
Table 12: Gains From Reducing Trade Costs

<table>
<thead>
<tr>
<th>Static Gains according to the ACR formula</th>
<th>50% Reduction in $\tau$</th>
<th>Relative to Autarky</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>U.S.</td>
<td>OECD</td>
</tr>
<tr>
<td>Static Gains in our Model</td>
<td>4.2%</td>
<td>5.0%</td>
</tr>
<tr>
<td>Change in growth rate (in % points)</td>
<td>0.17</td>
<td>0.17</td>
</tr>
<tr>
<td>Dynamic Gains</td>
<td>9.6%</td>
<td>15.5%</td>
</tr>
</tbody>
</table>

Note: Entries give the percentage increase in current year consumption (static) or in the present discounted value of consumption (dynamic) as a result of reducing tariffs from 1.50 to 1.25 (columns one and two) or reducing tariffs from 4 to 1.5 (columns three and four). The aggregate trade share at $\tau = 4$ is about 0.4%. We use a discount rate of 5% and linear utility.

of the OECD. The solid distribution is under our baseline ($\tau = 1.50$) and the dashed distribution is near autarky ($\tau = 4$). The relative quality distribution is markedly more dispersed near autarky. As a result, the trade elasticity is only 3 near autarky, whereas it is 5 under baseline tariff of $\tau = 1.50$. The degree of U.S. versus OECD comparative advantage across products is endogenously stronger near autarky. This is because ideas are not flowing as quickly between the countries when there is so little trade, so relative qualities drift apart. If we use a trade elasticity of 3 rather than 5, the ACR gains more than triple from 1.1% to 3.5%.

Figure 3 showed that the effect of trade liberalization on relative quality dispersion is smaller for small changes in trade. This can be seen by comparing the trade elasticity with $\tau = 1.25$ and $\tau = 1.50$ in the right panel of the Figure. Small changes in trade costs have only a modest effect on the comparative advantage gains from trade in our model. As a consequence, the ACR gains from cutting tariffs in half are closer to the static gains in our model.

When going from near autarky to $\tau = 1.50$, the trade share initially leaps

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15 We calculate local trade elasticities, varying the tariff rate by 10 percentage points.
from 0.4% to 24.6%. The trade share on impact overshoots the new steady state trade share of 10.2% precisely because of divergent qualities near autarky. Applying the ACR formula to the trade share on impact, the ACR static gains are 9.8% for the U.S., compared to 3.5% with a trade share of only 10.2%. As qualities converge toward each other in response to higher trade flows, the trade share eventually settles down to 10.2% and the trade elasticity rises from 3 to 5.

The last two rows in columns three and four of Table ?? present the growth and welfare gains from reducing tariffs from $\tau = 4$ to $\tau = 1.50$ including the effect on innovation. That is, the gains from going from autarky to current levels of trade. In our baseline model, this boosts long run growth by 46 basis points (from 2.54 to 3.00% per year). The consumption-equivalent dynamic welfare gains are 37% for the US and 104% for the rest of the OECD. Here again, the rest of the OECD gains more than the U.S. because the U.S. is the more innovative country.

## 7 Conclusion

We documented facts about export reallocation in U.S. manufacturing across categories and across firm in recent decades. Motivated by these facts, we constructed a two-country model of creative destruction and trade. In the model, foreign and domestic firms take over each other's markets more frequently when trade barriers are lower. This stimulates growth in the long run under exogenous innovation rates. Compared to (near) autarky, such dynamic gains are an order of magnitude larger than the usual static gains from trade.

We see several directions for future research. One is to explicitly incorporate frictions to reallocating workers in response to trade-induced creative destruction. Another route is to study events such as China joining the WTO. A third avenue would be to obtain more direct evidence on knowledge spillovers (e.g. the frequency of imitation of rich country producers by developing country producers, or of learning from domestic producers vs. foreign sellers in the local
We stressed that fitting the facts requires knowledge spillovers that are either embodied in trade or disembodied to explain observed export reallocation and trade elasticities. But whether trade or openness more generally has dynamic growth benefits hinges on whether the spillovers are largely embodied or disembodied.

We end with a conjecture about optimal innovation policy in our setting. Because of domestic knowledge spillovers, national governments may find it optimal to subsidize domestic R&D. But they might not internalize knowledge spillovers to foreign producers who build on domestic innovations. The world might need a “Global Technical Change Accord” to internalize these positive externalities, just as we need Global Climate Change agreements to internalize negative pollution externalities.

References


