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BETTER, FASTER, STRONGER: GLOBAL INNOVATION AND TRADE LIBERALIZATION

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Abstract—This paper estimates the effect on innovation of increased market access facilitated by trade liberalization. We use a novel empirical design that exploits tariff cuts during the 1990s, along with detailed data on innovation among firms from 65 countries. Our results reveal a large effect of tariff cuts on innovation as measured by patent data, suggesting that multilateral liberalization has promoted innovation and growth. These effects are not driven by the deterioration of innovation quality, and the results are robust to controlling for changes in the patent system and to industry-wide trends in innovation.

I. Introduction

TRADE policy liberalization opens up new markets abroad and therefore increases the effective size of the market. Economists have long known that the amount of invention is governed by the extent of the market.[1] However, there is currently no comprehensive empirical study of how improved market access through trade liberalization has affected worldwide innovation.

This paper seeks to fill this gap in the literature. Rather than focusing on a specific country, we present a novel global data set as well as empirical methodology that allows us to produce broad and systematic evidence on the impact of improved market access on worldwide innovation. Our approach enables us to disentangle this effect of trade liberalization on innovation from other institutional changes that often go hand in hand with trade policy.

Tariffs in both developing and developed countries came down substantially in the 1990s, leading researchers to name the period the Great Liberalization (Estevadeordal & Taylor, 2013). This was partly due to the completion of the GATT Uruguay Round in 1994, which resulted in substantial tariff cuts over the period 1995 to 2000. On average, developed country tariffs were cut from around 6% to 3%, while developing country tariffs were cut from almost 20% to 13% between 1990 and 2000.[2] This paper uses the Great Liberalization as a quasi-natural experiment to estimate the causal impact of improved market access on innovation among firms from 65 countries.

A major empirical concern in any study of the effect of market access on innovation is the endogeneity of tariffs, for example, that tariff reductions are likely to reflect cross-industry differences in lobbying intensity and industry concentration. We overcome this issue by exploiting variation in applied most favored nation (MFN) tariff cuts across a firm's export markets, which are likely exogenous to other determinants of innovation in the home country and industry of the firm. Specifically, we link tariff data to the initial industries and foreign countries the firm is exposed to through patent filing, in order to compute the average tariff cut faced by the firm. Intuitively, a firm x located in Germany and selling to the United States and Mexico is affected differently from a firm y in the same industry selling to China and South Korea because tariff cuts vary across those export markets. Conditional on industry-country trends, those MFN tariff cuts are unlikely to be caused by those two firms.

The data requirements for this exercise are large; one would ideally need a firm-level panel data set on innovation, along with detailed information on where firms are located and in which markets they sell in. To achieve this, we construct a global and comprehensive microlevel data set on patenting based on the global database PATSTAT, recently developed by the European Patent Office. We observe nearly every firm worldwide that files a patent, in which country (patent office) each files, along with its industry and home country affiliation, over four decades. We follow Aghion et al. (2016) and construct firm-level measures of market exposure by using information on patent filing in the years prior to the Uruguay negotiations. Compared to weights based on exports, these weights based on patent filing are potentially superior measures of market exposure because they are likely to reflect the firms' expectations of where their future markets will be. Moreover, we provide evidence that these patent weights

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[1] An early contribution is Schmookler (1966).

[2] Applied most favored nation (MFN) tariffs. See online appendix E for details.

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are strongly correlated with weights constructed from firm-destination level exports.

Our firm-level approach has a number of advantages. First, because initial foreign market exposure varies significantly within a country and narrowly defined industries, our global approach allows us to sweep out all home country-industry trends in innovation by fixed effects. In doing so, we tackle a set of well-known challenges. First, tariff cuts also lead to greater import competition in the firms' home market, which also affects innovation (Bloom, Draca, & Van Reenen, 2016). Second, the likelihood of patenting depends on a host of time-varying factors such as legal framework and technological characteristics of an industry.[3] Third, changes in tariff policy often go together with other government reforms, such as product market deregulation. Our empirical methodology allows us to isolate the impact of improved export market access and sidestep all of the above issues.

Our results are robust to a number of potential concerns. First, firms within the same industry with different export market exposure may also be differentially exposed to import competition from these countries. We show that controlling for the tariff cuts in a firm's home market does not change our main results. Second, one may worry that MFN tariff cuts in the destination country are contemporaneous to other policy changes in that country. An example of this is market size (or stricter patent enforcement, such as TRIPS). Being exposed to a high-tariff-cut country may be correlated with innovation simply because that country grows fast and increased market size fosters innovation. We show that we can either introduce a vector of destination fixed effects or, alternatively, use a control function approach that will eliminate this concern. Third, our long time period allows us to perform placebo tests; we test if treated firms exposed to high-tariff-cut countries typically always patent more.

Our results show that the Great Liberalization of the 1990s had a large, positive net impact on innovation. The overall estimates mask considerable heterogeneity across countries and industries. The impact of market access on innovation appears to be greater in developed compared to developing countries. Moreover, the effect is greater among countries that were initially more closed to trade.

One may question whether increased patenting reflects more innovation. The literature typically finds a strong correlation between patenting and research and development and between patenting and other measures of innovation. However, the concern remains that more trade could induce the need for greater protection of intellectual property rights (IPR), that is, that more patenting can simply be attributed to a "lawyer effect." To deal with this, we calculate citation counts for all firms in our data set to control for the quality of a patent and check whether average citations are falling in response to trade liberalization. The data reject this hypothesis; if anything, average citations are rising in response to better market access. Alternative measures correlated with the economic value of patents confirm that market access has not led to a reduction in patent quality.

The contributions of this paper are as follows. First, we develop a simple theory on trade and innovation and a novel empirical methodology consistent with the model. This allows us to isolate the effect of improved market access and produce broad and systematic evidence of the impact of trade liberalization on worldwide innovation over a decade with steep global tariff declines. Therefore, our analysis goes beyond the current literature that has primarily focused on unilateral or regional trade liberalization. Second, there is a large literature on the impact of trade policy on firm performance (e.g., TFP or labor productivity), but there is much less direct evidence on observable output-based measures of innovation such as patents; see Steinwender and Shu (2019) for a thorough review. We provide comprehensive evidence on the role of one of the mechanisms through which trade liberalization fosters improved firm performance and productivity growth. Third, we construct and analyze a novel, comprehensive, and global firm-level patent data set that has so far not been analyzed within the context of international trade.

Our analysis speaks to different strands of literature. Our work is related to the empirical analyses of firm-level data on the impact of trade liberalization on firm performance such as Amiti and Konings (2007), Goldberg et al. (2010), Khandelwal and Topalova (2011), and Loecker et al. (2016). Our work also indirectly relates to the literature on trade, import competition, and technology adoption. Bloom et al. (2016) analyze the effect of Chinese import competition on technology upgrading in Europe, while Autor et al. (2019) examine the impact of China competition on patenting in the United States.[4]

We also relate to Bustos (2011) and Lileeva and Trefler (2010), who analyze complementarities between trade liberalization and technological upgrading and innovation. What distinguishes our paper from these contributions is that (a) we develop a new identification strategy, (b) we offer evidence from global tariff cuts, and (c) we use patents as a direct output-based measure of innovation rather than input-based or survey information.[5]

Finally, our empirical approach is related to Aghion et al. (2016) and Calel and Dechezleprêtre (2016), who also use PATSTAT data but focus on very different questions, namely, the impact of environmental policies on technical change. Our choice of approach and results inform not only the literature on trade policy but also the broader literature on the effects of the drivers of innovation (Acemoglu & Linn, 2004; Aghion et al., 2005; Bloom et al., 2016 and Griffith, Harrison, & Simpson, 2010).

[3]Typical examples are regulatory changes in the patent system and differences across patent offices.

[4]Aghion et al. (2018), Boler, Moxnes, and Ulltveit-Moe (2015), Gopinath and Neiman (2013) and Halpern, Koren, and Szeidl (2015) also examine the link between firm performance and trade, but do not analyze trade policy.

[5]Steinwender (2015) also documents the relationship between access to export markets and productivity increases in the case of Spain.

The rest of the paper is organized as follows. Section II presents our theoretical framework. Section III lays out the empirical model and highlights econometric issues. Section IV describes the data and descriptives. Section V presents and discusses the empirical results, and section VI concludes.

II. Theoretical Framework

We aim to investigate the effect of foreign market access on firms' innovation. To do so, we start by presenting a basic economic framework to support the analysis and proceed by developing testable predictions for the relationship between market access and innovation.

Consider a firm i with productivity z_i, located in country m, and producing in industry j with constant returns to scale using only labor. Goods sold from m to a foreign country n in industry j are subject to an ad valorem tariff $T_{jmn} = \tau_{jmn} - 1 \geq 0$. Preferences across varieties within an industry are CES with an elasticity of substitution σ. This gives rise to a demand function $A_{in} p_{imn}^{-\sigma}$ in country n, where p_{imn} is the price charged by firm i in n and the demand shifter A_{in} may vary across firms and countries, and is exogenous from the point of view of an individual firm.[6] Producers engage in monopolistic competition, so that the price charged by firm i in market n is $p_{imn} = [\sigma/(\sigma-1)]\,\tau_{jmn} w_m/z$, where w_m is the wage of country m. For expositional clarity, we normalize the wage to 1, as it will be inconsequential for the remaining analysis. The profits from serving country n are $\pi_{imn} = (z/\tau_{jmn})^{\sigma-1} B_{in}$, where $B_{in} = (1/\sigma)\,[(\sigma-1)/\sigma]^{\sigma-1} A_{in}$. Global profits are then

$$\Pi_i = \sum_n \left[\left(\frac{z_i}{\tau_{jmn}} \right)^{\sigma-1} B_{in} \right].$$

The firm faces the problem of how much to innovate. Consider the simplest possible case where productivity z is proportional to the firm's stock of knowledge K_i, $z_i = \xi K_i$. We discuss the measurement of K_i in sections III and VB. Gaining new knowledge is costly, and we assume that the cost of obtaining a stock of knowledge K_i is $c(K_i) = \psi K_i^k$, where ψ determines average innovation cost and $k > \sigma - 1$ determines how quickly those costs rise with knowledge. The firm then chooses the optimal K_i that maximizes global net profits, $\Pi_i - c(K_i)$. In online appendix A, we show that the optimal knowledge stock is

$$K_i = \kappa \left(\sum_n \tau_{jmn}^{1-\sigma} B_{in} \right)^{1/[k-(\sigma-1)]}, \qquad (1)$$

where κ is a positive constant.[7]

Now consider a change in τ_{jmn} from one equilibrium to the next. Using the exact hat algebra approach as popularized recently by Dekle, Eaton, and Kortum (2008), we get

$$\hat{K}_i = \left(\sum_n \omega_{in} \hat{B}_{in} \hat{\tau}_{jmn}^{1-\sigma} \right)^{1/[k-(\sigma-1)]}, \qquad (2)$$

where $\omega_{in} = \pi_{in}(z) / \sum_o \pi_{io}(z)$ is the share of global profits coming from market n in the initial equilibrium, and the hat notation denotes the value in the counterfactual relative to the initial equilibrium, i.e. $\hat{x} \equiv x'/x$. Equation (2) highlights two important economic mechanisms. First, all else equal, foreign market access (lower τ_{jmn}) leads to both higher profits and a greater knowledge stock. Intuitively, a larger effective market means that a marginal improvement in productivity or quality yields a higher return. Second, our theory shows that tariff cuts in large markets matter more for innovation compared to tariff cuts in small ones and that the theoretically correct weight is the initial share of profits in that market.[8]

Before concluding this section, we briefly discuss three possible extensions of the model. First, in our model, tariff cuts matter only if the firm is already exporting to a destination, that is, if ω_{in} is strictly positive. In practice, firms may choose to both start exporting to country n and innovate as a response to tariff cuts in n. We investigate this case theoretically in online appendix B and empirically in online appendix I. Moreover, we show in online appendix G that there is a striking degree of persistence in ω_{in} over time, suggesting that exit or entry into new markets is limited in our data set.

Second, the approach chosen here means that we only analyze the impact of market access on innovation among existing firms, that is, we do not consider firm entry. This is guided by the empirical analysis and identification strategy. As will become clear, our unit of analysis is the firm, and we require presample data on ω_{in} for all the firms in the data set (which by construction excludes entrants from the analysis).

Third, we abstract from other economic factors that also affect innovation. Importantly, it is well known that a more competitive marketplace (e.g. coming from import competition) has an impact on innovation (Aghion, Harris, & Vickers, 1997, and Aghion et al., 2005). In this paper, we identify only the effect of market access on innovation; however, we flexibly control for the impact of import competition on innovation.

III. The Empirical Model

Based on the theoretical framework presented above, this section develops our main empirical model and discusses the identification strategy.

[6] Given the CES structure, $A_{in} = E_{in}/P_{jn}^{\sigma-1}$, where E_{in} is a demand shifter and P_{jn} is the CES price index of industry j.

[7] $\kappa \equiv \left[\xi^{\sigma-1}(\sigma-1)/(k\psi)\right]^{1/[k-(\sigma-1)]}$. The second-order condition for profit maximization is satisfied when $k > \sigma - 1$.

[8] Note that tariff cuts will also affect the price index and therefore $\hat{B}_{in}$. Our empirical approach will capture both the direct impact of $\hat{\tau}_{jmn}$ and the indirect impact of $\hat{B}_{in}$.

Online appendix C shows that equation (2) can be approximated by

$$\Delta \ln K_i = \beta \Delta \bar{T}_i + \varepsilon_i, \tag{3}$$

where

$$\Delta \bar{T}_i \equiv \sum_n \omega_{in} \Delta T_{jmn} \tag{4}$$

is the weighted average of tariff changes across all of firm i's export markets, T_{jmn} is the ad valorem tariff that country n levies on exports from country m in industry j, $\beta \equiv (1-\sigma)/[k-(\sigma-1)]$, and $\varepsilon_i \equiv [k-(\sigma-1)]^{-1} \sum_n \omega_{in} \Delta \ln B_{in}$. We proceed with this approximation because it is empirically more convenient to work with.[9] According to our framework, we expect that the knowledge stock is changing when weighted average tariffs in export markets decline or when weighted average demand (ε_i) rises. As demand shocks are unobserved in our data, ε_i will enter into the regression residual.

Endogenous tariffs. A potential concern is that ΔT_{jmn} (and $\Delta \bar{T}_i$) is endogenous because firms can lobby for improved market access through bilateral or regional trade negotiations. We solve this by instrumenting ΔT_{jmn} (and $\Delta \bar{T}_i$) with the applied MFN tariff rate cut ΔT_{jn}^{MFN} (see section IV), so that the instrumental variable is

$$\Delta \bar{T}_i^{MFN} \equiv \sum_n \omega_{in} \Delta T_{jn}^{MFN}.$$

The intuition for our instrument is as follows. The applied MFN tariff rate of country n is the rate that applies to all countries except the ones n has signed a trade agreement with. As such, it is unlikely that a firm i from country m has any influence over the MFN tariff of country n.

Sample period. The years 1992 to 2000 are defined as our baseline sample period. Therefore, the change in average tariffs facing firm i is $\Delta \bar{T}_i = \bar{T}_{i2000} - \bar{T}_{i1992}$, and the change in the knowledge stock of firm i is $\Delta \ln K_i = \ln K_{i2000} - \ln K_{i1992}$. The choice of sample period is motivated by the fact that tariff reductions agreed on during the Uruguay Round were gradually phased in from 1995 to 2000. In the data, we also observe tariff cuts before 1995; starting our sample in 1992 ensures that we capture the full impact of tariff reductions.[10] Our data also confirm that the 1990s were unique: the overall reduction in tariffs was much greater during the latter half of the 1990s compared to both earlier and later periods (see figure 2). Finally, we choose to work with long differences, 1992 to 2000, in our baseline specification because we want to allow for long time lags in the innovation response to trade liberalization. Long differences also eliminate serial correlation in the errors, since the averaging over periods ignores time-series information (see Bertrand, Duflo, & Mullainathan, 2004).

Outcome variable. In the model presented above, the outcome variable $\Delta \ln K_i$ is the change in the log knowledge stock. Our empirical counterpart is the cumulative patent count of a firm i until year t,

$$K_{it} \equiv \sum_{s=1965}^{t} p_{is}, \tag{5}$$

where p_{is} is the number of unique granted patents filed by firm i in year s. The outcome variable $\Delta \ln K_{it}$ gives the change in the log cumulative patent count between 1992 and 2000 and provides a measure of the innovation that takes place during this time period. Focusing on the change in the stock over a long time period smooths out lumpiness and 0s in the p_{it} variable. Indeed, in a given year, the median p_{it} is 0 while the maximum p_{it} is very large, suggesting that linear models are not adequate to model the data-generating process at the annual level.

Econometric concerns. Estimating equation (3) is challenging for a number of reasons. The first econometric concern is that the weighted average tariff reduction $\Delta \bar{T}_i$ (and the instrument $\Delta \bar{T}_i^{MFN}$) may be correlated with unobservable firm characteristics. For example, firms exposed to high-tariff-reduction countries may innovate more even in the absence of trade liberalization. We address this in three ways. First, we present a falsification test regressing knowledge growth during the 1980s on the same 1990s market access variable $\Delta \bar{T}_i$. Section VC shows that the estimated coefficient in this case becomes close to 0, suggesting that there are no pretrends driving our results.

Second, we address the concern by including home country-industry pair fixed effects (η_{jm}) in the regressions as well as controlling for a vector of preperiod firm characteristics (C_i).[11] Intuitively, we compare firms within the same narrowly defined industry, with the same home country, and with similar observed characteristics during the preperiod, but that differ in terms of their exposure to international markets, and we ask whether firms exposed to high-tariff-cut countries innovate more than firms exposed to low-tariff-cut countries. This approach also ensures that changes in the patent system or industry-specific trends in patenting are all differenced out. Therefore, our baseline approach will be based on the estimation of

$$\Delta \ln K_i = \eta_{jm} + \beta \Delta \bar{T}_i + C_i' \phi + \varepsilon_i. \tag{6}$$

[9] Online appendix, section C, evaluates the performance of the approximation.

[10] The year 1992 is also the first year for which the tariff data used in the analysis are available.

[11] Industries are defined at the NACE three-digit level. Presample covariates are home weights ω_i^H, the number of countries the firm is patenting in during the preperiod, $n_{i,Pre}$, and the log knowledge stock of the firm in 1985, $\ln K_{i,Pre}$.

A third way of addressing the concern that tariff reductions may be correlated with unobservable firm characteristics is by differencing out idiosyncratic firm trends. Specifically, we split the sample into our main sample period, ($t = 1$), and add a second period, ($t = 2$), and estimate the equation

$$\Delta \ln K_{i2} - \Delta \ln K_{i1} = \eta_{jm} + \beta \left(\Delta\bar{T}_{i2} - \Delta\bar{T}_{i1}\right) + C_i'\phi + \varepsilon_i. \tag{7}$$

Idiosyncratic growth trends in innovation that may be correlated with $\Delta\bar{T}_i$ are then differenced out. This is reminiscent of a triple differences model, as we compare the growth in the change in tariffs (two differences) across firms (third difference). We choose $t = 1$ as the baseline period 1992 to 2000 and $t = 2$ as the years 2000 to 2004.

A final concern is that the error term ε_i, a weighted average of country-specific demand shocks, may be correlated with trade liberalization. A case in point is the TRIPS agreement that strengthened intellectual property rights (IPR) among WTO members in the aftermath of the Uruguay Round. A positive correlation between tariff reductions and IPR strengthening could therefore produce biased estimates.[12] We solve this by using a control function approach and the fact that we observe aggregate patenting by industry and country, and this measure is itself determined by the unobserved shocks B_{in}. Specifically, we calculate the aggregate knowledge stock by industry j and home country h, $\mathcal{K}_{hjt} = \sum_{i\in\Gamma_{hj}} K_{it}$, where Γ_{hj} is the set of firms in industry j with h as home country, and construct the weighted average,

$$\tilde{\varepsilon}_i \equiv \sum_n \omega_{in}\Delta \ln \mathcal{K}_{nj}, \tag{8}$$

where $\Delta \ln \mathcal{K}_{nj} = \ln \mathcal{K}_{nj2000} - \ln \mathcal{K}_{nj1992}$. While home country-industry pair fixed effects control for innovation trends in firm i's home market, by adding $\tilde{\varepsilon}_i$ to our baseline estimation equation, we control for innovation trends in firm i's destination markets. For example, if a U.S. firm primarily exposed to the Indian market is innovating more because the Indian market is growing quickly (high $\Delta \ln B_{iIndia}$), then including $\tilde{\varepsilon}_i$ will control for this effect. An alternative approach is to use a vector of fixed effects for each of firm i's destination markets. We explore this approach, along with other robustness checks, in section VC.[13]

[12]TRIPS established minimum and common standards of IP protection to be adopted by all WTO members. While the institutions in the developed countries were little affected due to already strong IP protection, developing countries had to reform and strengthen their IP protection system to comply with new WTO rules.

[13]A potential remaining concern is that tariff cuts in an industry may be correlated with lowering nontariff barriers in the same industry. Our estimates would then reflect improved market access coming from both the former and the latter. However, data on nontariff barriers at disaggregated levels over a long-time horizon are not available, and it is therefore hard to separate the two mechanisms.

IV. Data

A. *Patents*

Our main data set is based on the European Patent Office's (EPO) Worldwide Patent Statistical Database (PATSTAT).[14] PATSTAT offers bibliographic data, family links, and citations of 90 million applications from patentees of more than 100 countries. It contains the population of all patents globally since the mid-1960s. The patent documents as provided by PATSTAT are a rich source of information. We observe the name of the applicant (patentee) and date of filing, publication, and if and when the patent was granted. We have information on citations, technology areas (IPC codes), and the research teams behind the inventions. A unique patent is typically filed in more than one country. We know the geography of the patent in the sense that we have information on both the home country of the patentee and the other countries in which the patent has been filed. Home country is the residence country of the applicant. Patentees can be private business enterprises, universities or other higher education institutions, governmental agencies, or individual inventors. In our final sample, 57% of patentees are firms, 40% are individual inventors and only 3% of the patentees belong to other types. We use all types in the analysis but commonly refer to them as firms throughout the paper.[15] More details on the sample and the construction of the data set are provided in online appendix D, while Abramovsky et al. (2008) provide a thorough review of the PATSTAT data and the patenting process.

Firm-specific knowledge stocks. PATSTAT allows us to construct an international firm-level data set and to follow the patenting activity of a firm through time. To measure the innovation activity of a firm i in year t, we use the number of granted patents dated by the earliest filing year, p_{it}.[16] Dating the patents by application filing date is conventional in the empirical innovation literature as it is much more closely timed with when the R&D process took place than the patent publication and grant date.[17]

Patenting is known to be highly correlated with innovation and R&D (Griliches, 1990). The advantages and limitations of patenting as a measure of innovation have been extensively discussed.[18] For our purpose, there is one major advantage

[14]The April 2015 version.

[15]We expect that individual inventors, who may typically be entrepreneurs about to start a new business, also respond to a change in foreign market access. Therefore, we choose not to limit the sample just to the patentees registered as firms.

[16]Not all filed patents are granted. We limit the analysis to patents that are granted to account for differences in quality. To be granted a patent, an innovation must satisfy three key criteria: it must be novel or new, it must involve an inventive step, and it must be industrially applicable.

[17]Patent applications are usually published 18 months after the first application.

[18]See OECD (2009), Griliches (1990), and Nagaoka, Motohashi, and Goto (2010) for reviews and discussion of patent data as innovation indicators.

of using patents: they are the only source of information that allows for a comprehensive firm-level analysis of innovation at a global scale. In section VB, we use different measures to control for the quality of patents as innovation indicators.

In our analysis, a patent corresponds to a unique invention, so filing the same patent in multiple locations does not inflate the patent count (p_{it}). Specifically, PATSTAT organizes patents into "patent families" that identify identical inventions filed in multiple countries.[19] An additional advantage of PATSTAT is that names of applicants are harmonized over the entire sample period, alleviating the concern that slight differences in the spelling of patentee names generate multiple patentee IDs.

Firm-specific weights. The empirical analysis relies on observing the firm-destination specific weights ω_{in}. These weights reflect the relative importance of a country n in the firm's total profits. Profits and sales are unobserved in our patent data, but we do observe in which markets a firm is patenting. As Aghion et al. (2016) pointed out, a patent-based weighting scheme may potentially be a superior measure because it reflects the firms' expectations of where their future market will be. We calculate these weights based on patent filings over the preperiod years 1965 to 1985. We use 1965 as the starting year because the number of patents in PATSTAT is limited in earlier years. The final year of 1985 was chosen because the Uruguay Round negotiations started in 1986; hence, the weights are not themselves affected by trade liberalization of the 1990s. Specifically, we define

$$\omega_{in} \equiv \frac{x_{in}}{\sum_k x_{ik}}, \tag{9}$$

where x_{in} is the number of patents issued by firm i in market n during the preperiod. Seeking intellectual property rights in a country is typically motivated by (future) profits in that market. There is strong empirical support that patent weights are highly correlated with sales weights (see Aghion et al., 2016). We provide additional empirical evidence on this in online appendix G. The weights are also remarkably persistent over time, even over a period of 20 years; see online appendix H. This suggest that time-invariant firm and country characteristics (e.g., country-specific entry costs on the supply side or idiosyncratic taste differences on the demand side) are limiting where firms export goods and file patents.

Firm characteristics. Information about patentees in PATSTAT is restricted to what can be retrieved from the patent applications. Our basic firm characteristics are industry affiliation (NACE Rev. 2 three-digit) and home country of the firm. Industry affiliation is assigned based on the technology area (IPC codes) of the patents filed by a firm. See online appendix D for more details.

[19]We use the DOCDB patent family.

B. *Tariffs*

The main source of tariff data is the UNCTAD Trade Analysis and Information System (TRAINS), which contains tariffs at the most disaggregated level of the Harmonized System (HS) for more than 150 countries. From this database, we extract the average applied MFN industry-level tariff (NACE three-digit) for the period 1992 to 2004, T_{jmt}^{MFN}, with 1992 being the first year for which a complete data set is available. We use these to calculate the firm-specific weighted average MFN tariffs, $\bar{T}_{it}^{MFN}$, which vary across firms, both because firms are exposed to different markets and because they belong to different industries. Online appendix E describes the procedure followed to calculate industry-level tariffs, while the online appendix F provides details about the historical background for tariff reductions during the 1990s.

The bilateral tariff, T_{jmnt}, is calculated as $T_{jnt}^{MFN} \times RTA_{mnt}$, where RTA_{mnt} takes the value 0 if there exists a trade agreement between m and n in year t and 1 otherwise. Our measure is an approximation of the true bilateral tariff; for some country pairs (e.g., EU countries), T_{jmnt} will equal the true bilateral tariff, while for others (e.g., the United States and Mexico), T_{jmnt} will be measured with error because trade agreement tariffs are not always 0. We use T_{jmnt} to calculate the firm-specific weighted average tariffs $\bar{T}_i$. The information on RTAs comes from the comprehensive data set on RTAs that is part of the CEPII gravity data.[20]

C. *Final Sample of Firms*

Our point of departure is a data set constructed on the basis of PATSTAT described in section IVA and online appendix D matched with industry-level tariff from UNCTAD TRAINS and information on regional trade agreements (RTAs).[21] Aiming to investigate the impact of the Great liberalization of the 1990s, our point of departure is the sample of firms residing in WTO countries with patent activity during the sample period, 1992 to 2000. We refer to this as the initial sample. During the 1992–2000 period, there were 763,581 firms filing 3,644,556 granted patents. Firms from WTO member countries were responsible for 85% of global patenting over this period.

Our empirical approach investigates the impact of market access at the intensive margin. Hence, we need to limit the analysis to firms that existed by 1992. The empirical strategy, moreover, requires information about the firms' patent filing abroad in the preperiod, as well as the trade barriers they face in their foreign markets. Given these requirements, we construct the final sample that forms the basis for the empirical analysis. The final sample consists of firms that (a) resided in countries that had become members of WTO (GATT) prior to 1995; (b) had applied for at least one granted patent by 1992

[20]See Head, Mayer, and Ries (2010) and Head and Mayer (2014) for details on the data set.

[21]We drop firms for which industry or home country affiliation were missing.

TABLE 1.—INITIAL VERSUS FINAL SAMPLE

	Initial	Final
$\sum_i \Delta K_{it}$	3,644,556	663,252
ΔK_{it}		
Mean	4.77	19.60
Median	1	2
Standard deviation	143.57	329.63
Number of firms	763,581	41,058

The table shows the aggregate increase in the knowledge stock from 1992 to 2000 along with the mean, median, and standard deviation of ΔK_{it} for the initial and the final sample of firms.

to ensure that the firm exists at the beginning of the sample period); (c) had been observed at least once in the preperiod (1965–1985) in order to be assigned weights ω_{in};[22] (d) had patent activity outside their home country and thus a positive weight ω_{in} in at least one foreign country; and (e) had issued patents only in countries where tariff data for their industry and export market is available.

The final sample consists of 41,058 firms, with 663,252 unique patents being granted between 1992 and 2000. The final sample captures roughly one-fifth of total patenting in the WTO over the sample period, 1992 to 2000. Our final sample consists of firms from 65 different countries and 54 different industries. Table 1 summarizes the difference between the initial and final samples, comparing total patenting in WTO countries to total patenting in the final sample. The reduction in the number of firms and patents in the final sample relative to the initial sample is primarily driven by restrictions (b) and (c); that is, the analysis is limited to firms that already exist. Table 12 in the online appendix shows additional moments from the initial and final samples. Importantly, the median number of citation-weighted patents in the initial sample is 0. This suggests that that majority of patents in the initial sample have negligible economic value; furthermore, the final sample is more representative of patents that generate economic value. Online appendix K provides additional details on countries and industries in the final sample and descriptives that show that the final sample is representative along these dimensions.

Note that we cannot distinguish between firm exit and zero innovation in our data. For example, if we observe zero patenting from 1995 and onward, then the stock of patents, K_{it}, will be constant for the remaining years of our sample. Therefore, our baseline result will capture the impact of market access on both the intensive margin (change in innovation among continuing firms) and extensive margin (firms that stop innovating).

D. Descriptives

Figure 1 shows the distribution of firms across home countries and industries (NACE 2-digit) in our sample. We note the dominance of Japan and the United States and by the industries machinery and equipment (28), computers, electronic and optical products (26), and other manufacturing (32). Tables 15 and 16 in online appendix K provide more details on patent counts and patenting firms across industries and countries.

Figure 2 shows the mean weighted average MFN tariffs, $\bar{T}_{it}^{MFN}$, for firms with the United States, Germany, Japan, and the United Kingdom as home country. There is a strong decline during the latter half of the 1990s; the average firm experienced a decline in weighted tariffs of around 3 percentage points during the 1990s. Also, the decline almost stops in the year 2000, consistent with the fact that Uruguay Round concessions were phased in until that year. The averages mask a considerable amount of heterogeneity. Figure 3 shows that the whole distribution of weighted tariffs across firms shifts markedly to the left from 1992 to 2000. We summarize the data in table 2, which shows the median, median, and standard deviation of $\bar{T}_{it}^{MFN}$, $\bar{T}_{it}$, and the log knowledge stock, $\ln K_{it}$, over time.

V. Results

A. Innovation and Trade Liberalization

We proceed by estimating the model presented in equation (6) and the alternative specification equation (7) using 2SLS. All specifications include home country-industry (NACE three-digit) pair fixed effects, which will control for aggregate (country and industry) trends in patenting. Columns 1 to 3 in table 3 show the results for our baseline specification. As described above, we instrument the tariff cut variable $\Delta\bar{T}_i$ with applied MFN tariff cuts $\Delta\bar{T}_i^{MFN}$. Column 1 has only fixed effects, and column 2 adds presample firm characteristics (the home weight, ω_{iH}, the number of countries the firm is patenting in during the preperiod, $n_{i,Pre}$, and log knowledge stock in 1985, $\ln K_{i,Pre}$), while column 3 also controls for aggregate destination trends $\tilde{\varepsilon}_i$, as explained in section III. Column 4 presents the results for the model described in equation (7), where we difference out idiosyncratic firm trends. The results are highly significant across specifications, with an estimated coefficient in the range of -1.68 to -3.22. These results strongly suggest that foreign market access leads to significantly higher innovation.

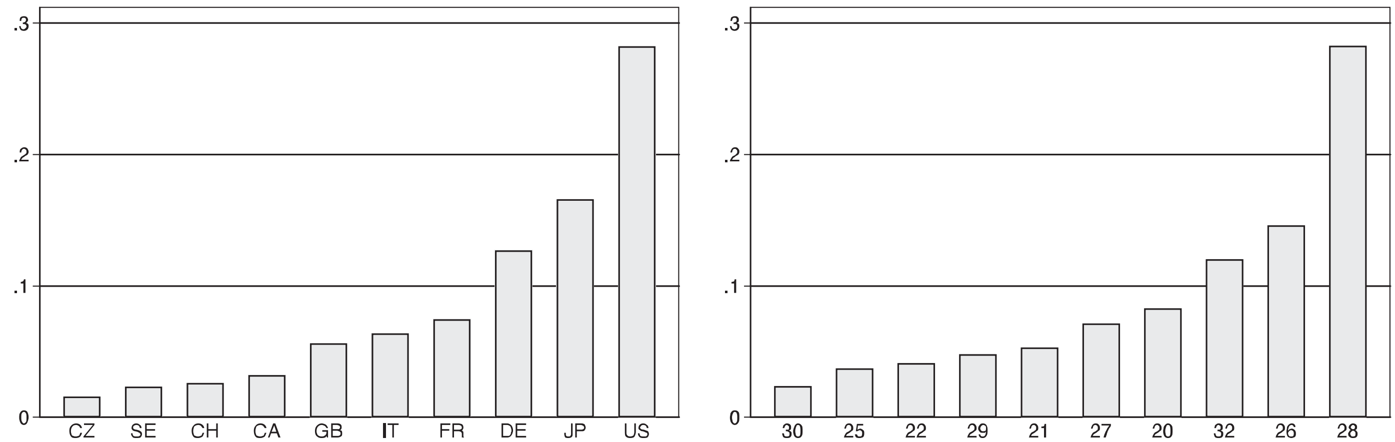
Table 13 in online appendix J presents the estimated coefficients on the various controls, first-stage estimates as well as reduced-form results of the specification with a complete set of controls. The instrument is strongly correlated with the endogenous variable. Figure 10 in the online appendix shows a binned scatterplot between the dependent variable and the instrument.

A semilog elasticity of -2.6 (in column 3) implies that a 1 percentage point reduction in tariffs causes a 2.6% increase in the knowledge stock of a firm over a period of eight years.[23]

[22]Both granted and nongranted patents are used for the construction of the weights ω_{in}. The weights reflect expectations on future markets. Therefore, it is the action of seeking intellectual property protection in a foreign country that is relevant rather than the final outcome of the application process.

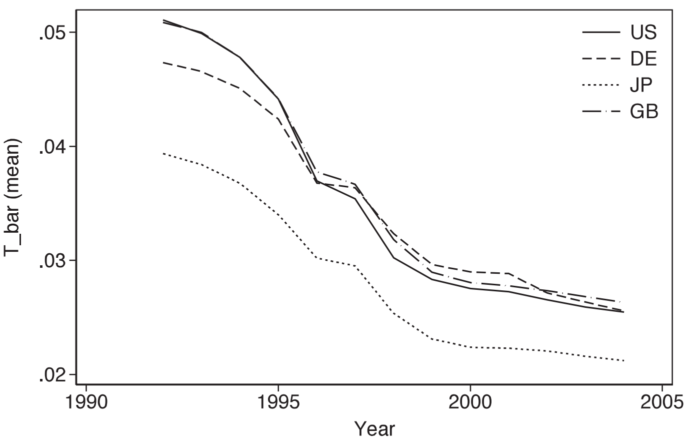
[23]Acemoglu and Linn (2004) find that a 1% increase in potential market size leads to approximately a 4% increase in the entry of new nongeneric drugs.

FIGURE 1.—SHARE OF PATENTING FIRMS BY COUNTRY AND INDUSTRY



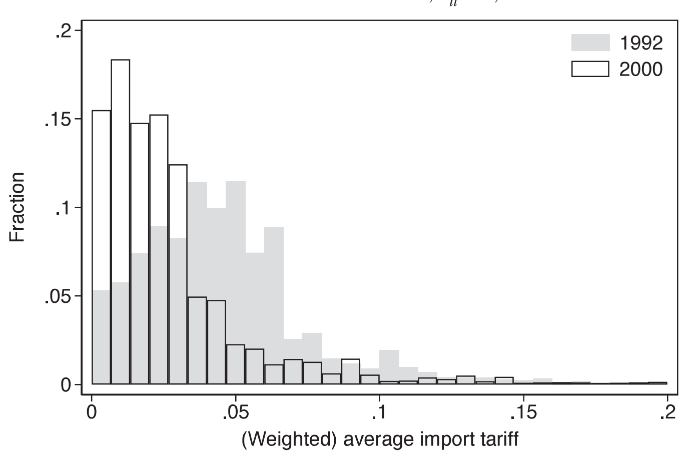
The figure shows share of firms by home country and NACE Rev. 2 two-digit industry for the period 1992 to 2000. Only the top ten countries and industries are shown.

FIGURE 2.—AVERAGE FIRM-SPECIFIC TARIFFS, $\bar{T}_{it}^{MFN}$



The figure shows the annual average $\bar{T}_{it}^{MFN}$ across firms according to home country.

FIGURE 3.—DENSITY OF FIRM-SPECIFIC TARIFFS, $\bar{T}_{it}^{MFN}$, IN 1992 AND 2000



For expositional purposes, the histogram is truncated at $\bar{T}_{it}^{MFN} = 20$.

As a simple back-of-the-envelope exercise, we ask how large our estimates are compared to the mean growth in the knowledge stock over the sample period. Our data show that over the period 1992 to 2000, the mean knowledge stock globally grew by 41%, while the mean reduction in the firm-specific tariff measure was 2 percentage points (mean of $\Delta\bar{T}_i$). Our results therefore suggest that roughly 13% ($2.6 \times 2/41$) of the observed increase in the knowledge stock can be explained by improved market access induced by trade liberalization. The back-of-the-envelope exercise holds all general equilibrium outcomes fixed; that is, the assumption is that the industry and country fixed effects do not themselves change in response to trade policy. General equilibrium responses are likely large, and therefore this exercise cannot identify the aggregate impact of the tariff cuts on innovation (which is outside the scope of this paper).

B. *Is Patenting a Good Measure of Innovation?*

As noted in in section IVA, one may argue that patents are an imprecise measure of knowledge and innovation. Patenting is not the only way to protect innovations. Another problem is that patent quality is highly heterogeneous. According to Nagaoka et al. (2010), roughly half of the patents owned by a firm are used either by that firm internally or licensed to others. The remaining patents are used for strategic reasons, such as attempts to block inventions by competitors. Therefore, it is possible that firms take out more patents without innovating more, for example, in response to import competition. If this were the case, one would expect that firms are taking out patents on their marginal innovations, so that the average quality of their patent stock is decreasing.

To address this issue, we use four proxies for patent quality: the number of citations, the size of the research teams behind a patent, the number of technology areas (IPC codes) to which a patent is attributed (patent breadth), and family size. Family size refers to the number of markets in which a patent is filed. We use citations because high-value inventions are more extensively cited than low-value patents (Harhoff et al., 1999). We include the size of research teams since a set of studies has associated the number of inventors listed in a patent with the economical and technological value of the patent (OECD,

TABLE 2.—MEAN, MEDIAN, AND STANDARD DEVIATION OF $\ln K_{it}$, $\bar{T}_{it}^{MFN}$, AND $\bar{T}_{it}$

	$\ln K_{it}$			$\bar{T}_{it}^{MFN}$			$\bar{T}_{it}$		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
1992	1.41	1.10	1.26	0.049	0.043	0.046	0.032	0.020	0.047
2000	1.83	1.61	1.33	0.029	0.021	0.036	0.019	0.010	0.033
2004	1.98	1.79	1.33	0.026	0.019	0.032	0.016	0.010	0.028

TABLE 3.—MARKET ACCESS AND KNOWLEDGE CREATION (2SLS)

Dep. Variable:	$\Delta \ln K_i$ (1)	$\Delta \ln K_i$ (2)	$\Delta \ln K_i$ (3)	$\Delta \ln K_{i2} - \Delta \ln K_{i1}$ (4)
Change in tariff ($\Delta\bar{T}_i$)	-2.81^{***}	-3.22^{***}	-2.62^{***}	-1.68^{***}
	(.47)	(.43)	(.45)	(.35)
Home country-industry FE	Yes	Yes	Yes	Yes
Firm controls	No	Yes	Yes	Yes
Destination market controls ($\tilde{\varepsilon}_i$)	No	No	Yes	Yes
1st stage F-statistic	2,372	1,204	1,029	600
Number of firms	41,058	41,058	40,805	40,805

Standard errors clustered by home country-industry in parentheses. Firm controls are presample firm characteristics: the home weight, ω_{iH}; the number of countries the firm is patenting in during the preperiod, $n_{i,Pre}$; and log knowledge stock in 1985, $\ln K_{i,Pre}$. The change in tariffs $\Delta\bar{T}_i$ is instrumented with the change in MFN tariffs, $\Delta\bar{T}_i^{MFN}$. Destination market controls controls for industry-specific innovation trends in a firm's destination markets. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

TABLE 4.—MARKET ACCESS AND INNOVATION QUALITY (2SLS)

Dep. Variable: $\Delta \ln \bar{Q}_i$	Citations (1)	Research Team (2)	IPC Codes (3)	Number of Markets (4)
Change in tariff ($\Delta\bar{T}_i$)	$-.68^{*}$	$-.30^{***}$	$-.16^{*}$	$.16^{**}$
	(.37)	(.09)	(.10)	(.07)
Home country-industry FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Destination market controls ($\tilde{\varepsilon}_i$)	Yes	Yes	Yes	Yes
1st stage F-statistic	774	1,344	1,030	1,029
Number of firms	26,886	37,539	40,747	40,805

Standard errors clustered by home country-industry in parentheses. Firm controls are presample firm characteristics: the home weight, ω_{iH}; the number of countries the firm is patenting in during the preperiod, $n_{i,Pre}$; and log knowledge stock in 1985, $\ln K_{i,Pre}$. The change in tariffs $\Delta\bar{T}_i$ is instrumented with the change in MFN tariffs, $\Delta\bar{T}_i^{MFN}$. Destination market controls controls for industry-specific innovation trends in a firm's destination markets. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

2009). The number of technical classes attributed to a patent application (patent breadth) has been found approximate the value of a patent portfolio (Lerner, 1994).

We calculate average quality of the knowledge stock as follows. Let q_p denote the number of citations three years after a patent p was filed, the number of inventors, the number of IPC codes, or the family size associated with patent p. The cumulative sum is then

$$Q_{it} = \sum_{s=1965}^{t} \sum_{p \in \Xi_{is}} q_p, \tag{10}$$

where Ξ_{is} is the set of firm i's patents filed in year s. The average quality of the knowledge stock is then calculated as $\bar{Q}_{it} = Q_{it}/K_{it}$. We proceed by using $\Delta \ln \bar{Q}_i = \ln \bar{Q}_{i2000} - \ln \bar{Q}_{i1992}$ as the dependent variable and estimate our baseline model again.

The results using all four proxies for quality are reported in columns 1 to 4 of table 4.[24] The results suggest that market access did not affect the quality of patents, that is, there is no evidence of a lawyer effect. If anything, the point estimates indicate that better market access may have increased the quality of patents, since it increased the average number of citations, average size of research teams, and patent breadth.

C. *Robustness*

Falsification test. A potential concern is that firms being exposed to countries with high tariff cuts always have higher patent growth compared to other firms. To address this concern, we perform a placebo test and regress knowledge growth during the 1980s, $\ln K_{i1988} - \ln K_{i1980}$, on trade policy changes during the 1990s, $\Delta\bar{T}_{i2000} - \Delta\bar{T}_{i1992}$.[25] The results are shown in the first column of table 5: the coefficient of interest is precisely estimated around 0, suggesting that there are no differential pretrends in patenting.

Triadic patents. We restrict our sample to triadic patents. These are patents filed at the three main patent offices: the

[24]The number of firms in the sample decreases when we use citations as a measure, since some firms have portfolios of patents that are never cited.

[25]The weighted average $\bar{T}_{it}$ is now calculated using weights ω_{in} based on a firm's patent portfolio until 1980. This ensures that the weights ω_{in} are not themselves determined by the dependent variable $\ln K_{i1988} - \ln K_{i1980}$.

Table 5.—Robustness (2SLS)

Dep. Variable: $\Delta \ln K_{it}$	Placebo (1)	Triadic Patents (2)	Alternate Dependent Variable (3)	Import Competition (4)	Input Tariffs	Destination Trends (5)
Change in tariff ($\Delta \bar{T}_i$)	.004***	−4.65*	−2.18***	−2.87***	−2.87***	−1.88***
	(.001)	(2.66)	(.54)	(.51)	(.51)	(.42)
Change in home tariff				1.89***	.60	
				(.48)	(.76)	
Change in input tariff					.02	
					(.01)	
Home country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Destination market controls ($\tilde{\varepsilon}_i$)	Yes	Yes	Yes	Yes	Yes	No
Destination country trends	No	No	No	No	No	Yes
1st stage F-statistic	626	833	2,262	563	508	2,027
Number of firms	21,568	2,405	29,320	37,980	37,980	41,058

Standard errors clustered by home country-industry in parentheses. Firm controls are presample firm characteristics: the home weight, ω_{iH}; the number of countries the firm is patenting in during the preperiod, $n_{i,Pre}$; and log knowledge stock in 1985, $\ln K_{i,Pre}$. The change in tariffs $\Delta \bar{T}_i$ is instrumented with the change in MFN tariffs, $\Delta \bar{T}_i^{MFN}$. Destination market controls controls for industry-specific innovation trends in a firm's destination markets. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

European Patent Office (EPO), the Japanese Patent Office (JPO), and the U.S. Patents and Trademark Office (USPTO).[26] Triadic patents are commonly used in the literature to retain only highly valuable inventions, and they provide a measure of innovation that is robust to administrative idiosyncrasies of the various patent offices. However, by limiting the analysis to triadic patents, the number of observations is reduced by around 94%. The results are shown in in column 2 of table 5. While we observe that the sample size is reduced to around 2,300 observations, our results on the impact of trade liberalization on the change in knowledge stock nevertheless remain significant, and the magnitude is close to the double as we limit our analysis to these presumably highly valuable inventions.

Alternative dependent variable. The change in log knowledge stock, $\Delta \ln K_i$, was used as the main outcome variable throughout the paper. An alternative measure that is often used in the literature is the log number of patents over the sample period 1992 to 2000, $\ln \Delta K_i$. Column 3 of table 5 shows that the results are similar to the baseline estimates.

Import competition. Tariff cuts also heighten import competition in firms' home markets. The impact of import competition is largely controlled for by the industry-country fixed effect η_{jm}. As an additional robustness check, we include the control variable $\sum_n \omega_{in} \Delta T_{jnm}$, that is, the weighted average import tariff in firm i's home market, using the same weights ω_{in}. The results are shown in column 4 of table 5. We observe that adding the control for import tariffs does not affect our baseline results. The results suggest that increased import competition had the opposite impact relative to improved market access: greater import competition reduced innovation.[27]

Input tariffs. We also repeat the exercise above using data on the firms' input tariff. Specifically, we calculate the input tariff of each industry and country-pair as $T_{jnm}^{Inp} = \sum_k \xi_{kj} T_{knm}$, where ξ_{kj} is the input cost share of industry j from sector k. The cost shares ξ_{kj} are from the World Input-Output Database (WIOD), using U.S. data from the year 2000.[28] The input tariff variable for a firm i in country m and industry j is then calculated as $\sum_n \omega_{in} \Delta T_{jnm}^{Inp}$. The results are shown in column 5 of table 5. The input tariff variable is not significantly different from 0. We observe that the correlation between the import and input tariff variable is high (0.82), which may explain why the variables are imprecisely estimated.

Destination country trends. The variable $\tilde{\varepsilon}_i$ was included in the regressions to capture patenting trends in destination countries. An alternative empirical strategy is to include destination country fixed effects in the regressions and estimate

$$\Delta \ln K_i = \eta_{jm} + \beta \Delta \bar{T}_i + +C_i' \phi + \sum_{n \in \Omega_i} \gamma_n + \varepsilon_i, \tag{11}$$

where γ_n is a fixed effect for destination n, and we sum over the set of countries Ω_i where the firm has nonzero weights during the preperiod. As an example, if all firms exposed to the Indian market (but not necessarily with India as home country) have high $\Delta \ln K_i$, then this will be controlled for by γ_{India}. Identification of β then only comes from within-country, across-industry variation in tariffs—that among firms exposed to the Indian market, some experience greater tariff reductions because they belong to an industry getting large tariff cuts in India. Destination country trends will therefore control for the possibility that firms exposed to India may patent more because of unobserved factors specific to India (e.g., growth in market size or strengthening

[26] See Dernis and Khan (2004) and Martinez (2010) for additional information about how triadic patent families are constructed.

[27] Our result on the impact of import competition is in line with the findings of Autor et al. (2019), while to some extent contrary to Bloom et al. (2016).

[28] We use a correspondence to convert ISIC industries to two-digit NACE revision 2 codes. Tariffs for nontraded input sectors k are normalized to 0.

TABLE 6.—MARKET ACCESS AND KNOWLEDGE CREATION BY QUARTILE OF COUNTRIES' CHARACTERISTICS (2SLS)

Dep. Variable: $\Delta \ln K_i$	GDP per capita (2)	Trade Intensity (% of GDP) (3)	Patent Stock ($K_{m,Pre}$) (4)
Change in tariff ($\Delta \bar{T}_i$)	5.02*	−3.28***	52.28***
	(2.92)	(.59)	(.45)
$\Delta \bar{T}_i \times Q_h^2$	−3.01	1.18*	−48.53***
	(3.01)	(.67)	(2.20)
$\Delta \bar{T}_i \times Q_h^3$	−7.36**	2.34***	−54.28***
	(2.92)	(.81)	(.65)
$\Delta \bar{T}_i \times Q_h^4$	−7.96***	2.63***	−54.97***
	(2.96)	(.84)	(.67)
Home country-industry FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Destination market controls ($\tilde{\varepsilon}_i$)	Yes	Yes	Yes
1st stage F-statistic	85-9819	30-647	205-572
Number of firms	39,679	39,679	40,805

Standard errors clustered by home country-industry in parentheses. Firm controls are presample firm characteristics: the home weight, ω_{iH}; the number of countries the firm is patenting in during the preperiod, $n_{i,Pre}$; and log knowledge stock in 1985, $\ln K_{i,Pre}$. The change in tariffs $\Delta \bar{T}_i$ is instrumented with the change in MFN tariffs, $\Delta \bar{T}_i^{MFN}$. Destination market controls controls for industry-specific innovation trends in a firm's destination markets. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

TABLE 7.—MARKET ACCESS AND KNOWLEDGE CREATION BY QUARTILE OF FIRM INNOVATIVENESS (2SLS)

Dep. Variable:	Initial Patent Stock	Quality Adjusted Initial Patent Stock
Change in tariff ($\Delta \bar{T}_i$)	−2.70***	−.83***
	(.41)	(.25)
$\Delta \bar{T}_i \times Q_{ijn}^2$	.76	−1.02
	(.50)	(.66)
$\Delta \bar{T}_i \times Q_{ijn}^3$	−.67	.28
	(.46)	(.62)
$\Delta \bar{T}_i \times Q_{ijn}^4$	.76	2.39***
	(.94)	(.72)
Home country-industry FE	Yes	Yes
Firm controls	Yes	Yes
Destination market controls ($\tilde{\varepsilon}$)	Yes	Yes
1st stage F-statistic	140-648	278-449
Number of firms	40,805	38,671

Standard errors clustered by home country-industry in parentheses. Firm controls include dummies for the second, third, and fourth quartile of the firm size distribution and presample firm characteristics: the home weight, ω_{iH}; the number of countries the firm is patenting in during the preperiod, $n_{i,Pre}$; and log knowledge stock in 1985, $\ln K_{i,Pre}$. The change in tariffs $\Delta \bar{T}_i$ is instrumented with the change in MFN tariffs, $\Delta \bar{T}_i^{MFN}$. Destination market controls for industry-specific innovation trends in a firm's destination markets. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

of IPR). The estimated coefficient in column 6 in table 5 shows that β is still highly significant.

D. Heterogeneity

Finally, we explore potentially heterogeneous effects across countries and firms. We start by exploring country heterogeneity by specifying

$$\Delta \ln K_i = \eta_{jm} + \beta \Delta \bar{T}_i + \sum_{q=2}^{4} \beta^q \left(\Delta \bar{T}_i \times Q_h^q \right) + C_i' \phi + \varepsilon_i, \tag{12}$$

where Q_n^q refers to the qth quartile and h to the type of characteristic that is investigated. We consider three country characteristics: income per capita, trade intensity, and innovativeness. As measures of these, we use GDP per capita, export plus import in % of GDP, and country-level patent stock, respectively. While the latter is based on our own calculations, we use data provided by the World Bank for the measures of GDP per capita and trade intensity.[29]

We split countries into quartiles based on the relevant characteristic. All quartiles are calculated using 1986 data. We estimate equation (12) by 2SLS using the same approach as in the baseline and report the results in table 6.

Income. Focusing on GDP per capita, we find that the effect of market access is imprecisely estimated in the lowest two income quartiles. The effect is positive and significant in the third and fourth quartiles of the income distribution, suggesting that market access has a stronger impact on innovation in developed countries compared to developing countries.[30]

Trade intensity. The effect of market access on innovation is strongest in the lowest quartile in terms of trade intensity and decreases in higher quartiles (Q1>Q2>Q3>Q4). This suggests that market access has a bigger impact on innovation on countries that are initially relatively closed to trade.

Innovativeness. The results on innovativeness mirror the results on GDP per capita; for the two first quartiles, improved market access has a zero or negative impact on innovation, while for the third and fourth quartiles, the impact is positive.

Next, we consider the role of firm-level heterogeneity focusing on firm innovativeness. We split firms into quartiles of firm innovativeness, measured relative to industry country average innovativeness, letting Q_n^q refer to the qth quartile and h to the type of measure. We use two measures of innovativeness: firms' initial (1985) patent stock relative to industry-country average and firms' quality-adjusted initial patent stock relative to industry-country average.[31] We proceed by estimating

$$\Delta \ln K_i = \eta_{jm} + \beta\, \Delta \bar{T}_i + \sum_{q=2}^{4} \beta^q \left(\Delta \bar{T}_i \times Q_{ijn}^q \right) + \sum_{q=2}^{4} \delta^q \times Q_{ijn}^q + C_i' \phi + \varepsilon_i, \tag{13}$$

based on the same IV approach as in the baseline and report the results in table 7. The effect of greater market access is positive and significant for firms in all quartiles. The impact

[29] GDP per capita (constant 2010 US$) with indicator ID: NY.GDP.PCAP.KD, and Trade (% of GDP) with indicator ID: NE.TRD.GNFS.ZS.

[30] The results in the literature on developed versus developing countries are mixed; see Steinwender and Shu (2019).

[31] We calculate the quality-adjusted patent stock for each firm using citations as a measure of patent quality as follows: $C_{ijnPre}/\overline{C}_{jnPre}$, where C_{ijnPre} is firms' citation-weighted patent stock in the preperiod and $\overline{C}_{jnPre}$ is the average citation-weighted patent stock in firms' industry and country.

appear to be stronger in the first and third quartiles; however, the standard errors for the interaction terms are relatively large.

When we measure innovativeness in terms of quality-adjusted patent stock, the effect of improved market access appears to have the strongest impact on innovation in the lowest two quartiles.

VI. Conclusion

We set out to analyze the impact of improved market access facilitated by trade agreements on worldwide innovation. To do so, we use the decline in tariffs during the 1990s in the aftermath of the GATT Uruguay Round and a comprehensive global data set of patenting. Our results show that the Great Liberalization of the 1990s had a large, positive net impact on innovation. Our results indicate that a 1 percentage point tariff cut in export markets leads to 2% to 3% growth in firms' knowledge stock, suggesting that trade policy was an important factor driving global innovation in the 1990s. Our findings underscore the importance of trade liberalization for firms' long-term performance and for aggregate economic growth. They point to the large, dynamic gains from trade—gains that are typically not observed and therefore neglected in empirical analyses.

Our estimates are robust to a set of econometric issues, and in particular we provide evidence in support of patents as a useful measure of innovation. While the results are directly relevant for the analysis of trade policy, they also add to the broader literature on economic factors that govern innovation and growth.

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