# Labor-induced Technological Change: Evidence from Doing Business in China

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**Abstract**

We study how the change in the price of labor affects the direction of technological change using a novel measure decomposing innovations into products (new goods) and processes (lower production costs). Using the 1999 U.S.-China agreement as a shock that lowered effective labor cost, we find that U.S. firms operating in China decrease their share of process innovations by 9% and that this adjustment is driven by lower process innovation. We obtain the same results using a staggered loosening of restrictions on foreign ownership across industries in China over 1995-2012. This suggests that cheap abundant labor substitutes for labor-saving innovation.

**JEL classification: O33, J31, L23**

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*Manufacturers who had been automating U.S. and European factories to shave labor costs stopped once they set up in China. (WSJ, 11/23/2015)*

# I Introduction

One of the central questions of economic growth is how labor scarcity and high wages alter the direction of technological change and whether they encourage technological advances. Basic intuition suggests that if a production factor becomes more expensive, the demand for it decreases, and some of this adjustment takes place by technology substituting for tasks performed by this factor, which then induces innovation more broadly.[1] For example, according to Habakkuk (1962), it was the scarcity of labor in the nineteenth century United States that obliged American manufacturers to install new types of labor-saving machinery, as compared to British manufacturers, and led to the future continuous progress of American industry. In contrast, according to many canonical macroeconomic models, when new technologies are embodied in capital goods, labor scarcity and high wages slow down technological progress. Theoretical predictions are in fact ambiguous: Acemoglu (2007) shows that an increase in the abundance of a production factor can make the technology relatively biased toward or against this factor, while Acemoglu (2010) shows that labor scarcity may induce or discourage technological progress depending on the nature of technology.

In this paper, we examine how the change in the price of labor affects the direction of technological change, focusing on the two main types of innovation: product and process.[2] Product innovation results in new goods while process innovation refers to new methods that lower production cost (Scherer 1982, 1984; Link, 1982; Eswaran and Galini, 1996).

[1] In *The Theory of Wages*, John Hicks argues: "a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind–directed to economizing the use of a factor which has become relatively expensive" (1932, p. 124).

[2] We delineate product and process innovations by classifying firms' patent claims into product and process claims. To classify the claims, we parse the structured-text documents of the universe of patent grants issued by the United States Patent and Trademark Office.

Specifically, we ask whether and how U.S. firms changed their process-product innovation mix in response to a decrease in their effective labor cost driven by improved ability to harness cheap and abundant Chinese labor. Our key argument is that U.S. firms consider two alternative ways to lower their production cost: substituting Chinese for U.S. labor and investing in process innovation. Our hypothesis is that, when Chinese labor becomes more attractive, the return on investment in process innovation relatively decreases, which makes the U.S. firms invest less in process innovation. We document that, in response to lower effective labor cost, U.S. firms operating in China change their process-product innovation mix by pursuing less process innovation.

A major benefit of operating in China for U.S. firms is a large supply of low-cost labor. Average Chinese factory-worker hourly wages are estimated to be 2%-3% of the corresponding U.S. wages in the 2000s.[3] However, U.S. firms operating in China cannot capture the benefit of low wages because Chinese partners (for example, joint venture counterparts, suppliers, distributors) capture a large share of the profits of U.S. firms' subsidiaries in China.[4] As a result, the effective labor cost of U.S. firms from their Chinese operations does not only depend on the wage paid to Chinese workers, but also on the share of profits of Chinese subsidiaries that is captured by the Chinese partners.

To identify an exogenous change in U.S. firms' labor cost, we rely on the *1999 U.S.-China bilateral agreement* which decreased effective labor cost of U.S. firms operating in China. The agreement, which was largely unanticipated due to the turbulent political landscape, lifted U.S. firms' restrictions on doing business in China, such as: the removal of local content and export performance requirements, the withdrawal of FDIs' approval being

[3]"China's average manufacturing wages, at about $0.25 per hour, are about one-fifth as great as Mexico's, and about one-fiftieth as much as total compensation for manufacturing workers in the United States. China's labor force is 18 times that of Mexico and five times that of the United States" (CSR Report for Congress, 2000).

[4]The idea that China is a prominent example of hold-up problems due to the fact that foreign companies have to deal with local partners is not new. In *Poorly Made in China*, Midler (2009) describes how Chinese suppliers extract surplus from Western companies by manipulating prices and quality and argues that solutions like relationship contracting were not effective in the case of China. See also discussion in Antràs (2003, 2005, 2013).

conditional on the usage of domestic suppliers, or the liberalization of distribution services. While a large share of the profits of Chinese subsidiaries accrued to Chinese partners before 1999, the agreement increased the share of the profits the U.S. firms capture post-1999, effectively reducing their labor cost. In our analysis, we therefore compare the effect of the *1999 U.S.-China bilateral agreement* on U.S. high-patenting firms with a subsidiary in China prior to the agreement (treated) relative to U.S. high-patenting firms with no such presence (control).

We find that, after 1999, the treated firms have a lower share of process to total innovations relative to the control firms by 3 percentage points compared to pre-treatment years, which is a 9% reduction relative to the median ratio. We show that this change in the process-product innovation mix is driven by a lower level of process innovation, which is 19% lower for the treated firms. In contrast, the agreement has no differential effect on the level of product innovation of the treated relative to control firms.[5] These results suggest that cheap Chinese labor decreases return to investing in labor-saving technological innovation, namely innovation substituting for more "expensive" U.S. workers.

To provide support for the economic mechanism we consider, we examine subgroups where we expect to observe differential treatment effects. First, we exploit cross-sectional variation in the equity shares of U.S. firms vis-à-vis their Chinese counterparts in the Chinese subsidiaries. Since the effect we are identifying operates through the ability of U.S. firms to capture a higher share of the subsidiaries' profits, we expect the treated firms with higher U.S. equity relative to Chinese equity to respond more to the agreement. As predicted, we find a larger negative effect on the process-product innovation mix and the level of process innovation for such treated firms. Second, consistent with the intuition that our findings are due to the labor channel, we find that the treatment effect is smaller when the subsidiaries of the U.S. firms in China expect to pay relatively higher wage bills. To proxy for higher expected wage bills, we require the subsidiary to be located in Chinese

[5]This evidence suggests that the U.S. firms with presence in China do not increase the rate of product innovation by more due to an improved access to the Chinese large and rapidly developing market.

counties with the growth rate of minimum wages in 1998 above the sample median and also the number of workers employed by the subsidiary to be above the sample median.

In our regressions, we control for time-invariant firm characteristics, by including firm fixed effects, for time-varying firm characteristics, by including firm-level controls, and for time-varying industry characteristics, by including interacted industry and year fixed effects. Our key identifying assumption is that, conditional on these controls, the assignment of firms into the treated and control group is "as good as random." We conduct several analyses to show support for this assumption. First, we compare summary statistics of firm characteristics for our treated and control samples in 1998 and show that there are no systematic differences pre-treatment. Second, we find no significant effect of the agreement in pre-treatment years, while the effect persists after the shock. Third, when we control for potential differential trends between the treaded and control firms by interacting the value of the dependent variable in 1998 with a full set of year dummies, our results continue to hold. These results suggest that there are no pre-trends in our data. We also repeat our analyses using a matched control sample and obtain very similar results.

In our robustness checks, we sort firms into placebo treated and control groups based on whether they have a subsidiary in Asia excluding China in 1998, adding a placebo interaction term to our regressions. If our results are driven by an omitted variable, such as productivity shocks that are common to countries in similar geographies, we should observe a negative and significant coefficient on the placebo interaction term, but we do not. Another potential concern is that we are capturing the effect of Chinese import competition on technological change. Bloom, Draka, and Van Reenen (2015) find a positive effect of Chinese import competition on the level of innovation of European firms. To the extent that our treated and control firms might be differentially affected by import competition, it is possible that a response to Chinese imports is driving our results. To address this concern, we show that Chinese import competition has no differential effect on the process-product innovation mix and on the levels of process and product innovations.

To further establish causality, we examine whether our results are robust to using an

alternative setting. We use the variation across industries and over time in ownership restrictions imposed on foreign investments by the Chinese government. The source of this information is the Foreign Investment Industry Catalogues issued six times in the 1995-2012 period. Similar to our main experiment, the staggered loosening of restrictions on foreign ownership implied by the catalogues changes the split of the profits of Chinese subsidiaries in favor of U.S. firms, effectively reducing labor cost. We find that the loosening of restrictions decreases the ratio of process to total innovations and the level of process innovation for high-patenting firms with subsidiaries in China as compared to those with no interest in China, while there is no differential effect on the level of product innovation.

Prior studies analyze the effect of trade between low-wage and developed countries on various outcomes of import-impacted firms, such as, employment and wages (Autor, Dorn, and Hanson, 2013; Acemoglu, Autor, Dorn, and Hanson, 2014; Pierce and Schott, 2015; Autor, Dorn, and Hanson, 2016), innovation (Bloom, Draka, and Van Reenen, 2015), performance and survival (Bernard, Jensen, and Schott, 2006; Hombert and Matray, 2015). China garners significant attention in this literature due to its size and rapid trade growth. Also related are papers examining the impact of regulatory frictions on international trade and investment. Moran (2001) studies the effects of domestic-content, joint-venture, and technology-sharing requirements on production transfer to developing countries. Desai, Foley, and Hines (2004) find that when ownership restrictions are lifted, intra-firm trade and technology transfer of U.S. multinationals increase. Antràs (2005) shows that the trade-off between a lower production cost and contract incompleteness in international transactions leads to less new products being produced in low-production cost countries. Finally, our paper is related to the literature on the adoption of new technologies and the patterns of international specialization (Ciccone and Papaioannou, 2009; Caselli and Coleman, 2006; Nelson and Phelps 1966). We add to these literatures by studying an unexplored issue—how the increasing availability of China's cheap labor for global production affects technological choices of firms in developed countries.

There is also a limited number of empirical studies examining the relation between production factors and the adoption of existing technologies (Acemoglu and Finkelstein,

2008) or development of new technologies (Newell, Jaffe, and Stavins, 1999; Hanlon, 2015). Acemoglu and Finkelstein (2008) show how regulatory changes in the U.S. healthcare sector affect the capital-labor mix and technology adoption in hospitals. Newell et al. (1999) look at the effect of energy prices on the direction of innovation. Hanlon (2015) studies the response of technology to a change in the type of cotton used in the British cotton textile industry due to the U.S. Civil War and finds that an increase in the supply of Indian cotton induced technological changes that augmented Indian cotton. Our study shows that the price of labor is an economically important determinant of of the process-product innovation mix, which is consistent with the view that changes in the relative prices of the factors of production drive the direction of technological change.

The paper is organized as follows. Section II describes our measures of the direction of technological change. Section III gives details on the 1999 U.S.-China bilateral agreement and section IV describes the sample. In sections V-VII, we present the main identification approach using the 1999 U.S.-China agreement to study the effect of labor cost on the direction of technological change. Section VIII presents the alternative experiment, and section IX concludes.

# II Data and Construction of Variables

We measure firms' technological choices by looking at their process-product innovation mix. By definition, a process innovation describes a new way to produce an existing good, while a product innovation describes a new good that did not exist before. Prior literature argues that a process innovation is aimed at improving a firm's own production methods in order to lower its production cost, while a product innovation is an improvement sold to others—either to consumers or to other firms (Scherer 1982, 1984; Link 1982; Cohen and Klepper, 1996; Eswaran and Gallini, 1996).

To proxy for firms' process and product innovations, we examine the output of corporate R&D activities as measured by patents, the exclusive rights over an invention of a product or a process (Griliches, 1990). We collect information from the complete set of patent grant

publications issued weekly by the United States Patent and Trademark Office (USPTO) from January 1990 to December 2012.[6] In this way, we obtain full texts of the universe of utility patents awarded by USPTO to U.S. and international companies, individuals, and other institutions. We parse the structured-texts of patent grants to first identify the section that contains patent claims, and next to classify each claim within this section as process or product. We are also able to classify claims into independent (i.e., those that stand alone and do not reference any other claim) or dependent.[7] Patent claims define—in technical terms—the scope of protection conferred by a patent, and thus define which subject matter the patent protects. Claims are critical defining elements of a patent and are the primary subject of examination in patent prosecution. Claims are also crucial in patent litigation cases.

To measure a firm's process-product innovation mix, we define *Share of process innovations*$_{it}$ as the ratio of the number of process claims to the total number of claims that are contained in patents applied for by firm $i$ in year $t$. Alternatively, we use *Share of process innovations_Independent*$_{it}$ defined analogously using independent claims only. To measure the quantity of process (product) innovation output, we define *Process innovations*$_{it}$ (*Product innovations*$_{it}$) as the natural logarithm of one plus the number of process (product) claims that are contained in patents applied for by firm $i$ in year $t$. Alternatively, we use *Process innovations_Independent*$_{it}$ and *Product innovations_Independent*$_{it}$ that are based on counts of independent process and product claims, respectively. In Appendix A, we provide summary statistics and validation checks for our innovation variables.

We also classify each patent as: i) a process patent, if all patent's claims are process claims; ii) a product patent, if all patent's claims are product claims; iii) a process-apparatus patent, if the first patent's claim is a process claim and there exists at least one independent claim that is a product claim; iv) a product-method patent, if the first patent's claim is a product claim and there exists at least one independent claim that is a process claim.

[6] We download the publications from the 'United States Patent and Trademark Office Bulk Downloads' page hosted by Google Inc. at http://www.google.com/googlebooks/uspto.html.

[7] A detailed description of how we distinguish claim types is provided in Appendix A.

At the patent level, our measure of a firm's process-product innovation mix is *Share of process innovations_Patent*$_{it}$ defined as the sum of the number of process and process-apparatus patents (or, alternatively, the sum of the number of process, process-apparatus, and product-method patents) divided by the total number of patents applied for by firm $i$ in year $t$.

To assign patents to firms in Compustat, for each patent, we identify patent assignees listed on the patent grant document, the country of these assignees, and the indicator of whether each assignee is a U.S. corporation, a non-U.S. corporation, an individual, or a government body. Using this information, we match patents to firms in Compustat. Our matching algorithm involves two main steps. First, we standardize patent assignee names and firm names—focusing on unifying suffices and dampening the non-informative parts of firm names. Second, we apply multiple fuzzy string matching techniques to identify the firm, if any, to which each patent belongs.[8]

# III 1999 U.S.-China Bilateral Agreement

The bilateral agreement signed between the U.S. and China in November 1999 was a landmark in the economic relations of the two countries and it paved the way to China's entry into the World Trade Organization (WTO). This agreement involved significant concessions from China, including tariff reductions, trade barrier removals, and the elimination of a number of restrictions on investment by U.S. firms.

The agreement was unexpected due to turbulent political relations between the two countries. Figure B1 in Appendix B presents the timeline of the events leading to the agreement (Devereaux and Lawrence (2004) provide a detailed description of the events). In mid-1997, the U.S. puts aside multilateral negotiations and starts bilateral talks with China—a decision driven mainly by political reasons. In 1998, little progress is being made.

[8]See Bena, Ferreira, Matos, and Pires (2016) for a more complete description of the matching procedure and a comparison of the matches to those in the NBER patent database. Note that the NBER patent database provides GVKEY-patent number links for patents awarded till 2006, while our matching is based on patents awarded till June 2013.

A milestone in the talks is the visit of Premier Zhu Rongji in the U.S. in April 1999, when he made—for the first time—significant concessions. These concessions galvanized U.S. firms to start unprecedented lobbying for the agreement, as they now realized its benefits. No agreement was signed however, and the negotiations were seriously threatened a few weeks later when U.S. mistakenly bombed the Chinese embassy in Belgrade. The agreement was finally signed on November 15, 1999 when the U.S. Trade Representative (USTR) Charlene Barshefsky visited China. To emphasize the uncertainty surrounding the negotiations, it is worth mentioning that USTR threatened to leave China three times and the negotiations were completed only after she decided to stop at the trade ministry on her way to the airport.

Historically, U.S. firms operating in China faced numerous restrictions and government interventions that were substantially alleviated by the newly signed agreement. Specifically, China lifted ownership restrictions on foreign investment and agreed to comply with the WTO Trade Related Investment Measures agreement upon accession. China also ceased to impose trade and foreign exchange balancing requirements, local content requirements (which require foreign firms to use domestic materials and parts for production), and export performance requirements (which require the export of a specified percentage of production volume). China committed that approval of investment will not be conditioned on whether domestic suppliers of such products exist, or requirements of any kind such as offsets, transfer of technology, production processes, or the conduct of research and development in China. The terms and conditions of any such transfers will be agreed between the parties to the investment without government interference. Furthermore, China committed to ensure fair competition between private and state-invested enterprises and liberalize distribution services, allowing foreign firms to set up wholly-owned distribution, sales, shipping, and service networks. Overall, the agreement secured that China is moving toward "rule of law" and will be held accountable for the contracts that it makes (Charlene Barshefsky, 18 November 1999).

# IV Sample Construction and Summary Statistics

Our sample consists of all Compustat firms that are active in innovation around the time of the event and do not exit the Compustat sample immediately after the event. Specifically, we pick November 15, 1999, i.e., the date when the U.S.-China bilateral agreement is signed, as the date of the event, and require that firms have non-missing assets during four years around the event (1998-2001) and apply for a minimum of 20 patents in this four-year period. For this sample of firms, we hand collect information on which firms have subsidiaries in China as of 1998 from 10-K filings. If the 10-K filing is not available for a given firm at the time of the event, the firm is dropped from the sample. The treated group consists of firms with a subsidiary in China as of 1998, while the control group consists of firms with no such presence in China.

Our sample period starts in 1995 and ends in 2004, thereby using 10 years of data around the event. Our main dependent variable *Share of process innovations*$_{i,t}$ is defined for firm-years with at least one patent and it provides a meaningful measure of the changes in the process-product innovation mix over time only for firms with a nontrivial number of patents. Our main results are therefore based on a sample of high-patenting firms, namely those that applied for 150 patents or more with the USPTO during our sample period.[9]

Table 1 provides summary statistics of our sample firms' patents. On average, a patent has 19.6 claims, of which 7.4 are process, 12.3 are product, 3.4 are independent, and 16.2 are dependent.[10] Table 2 provides summary statistics of our sample firms' characteristics. On average, a firm in our sample has assets of \$13.6 billion, sales of \$10.4 billion, profits of \$1.8 billion, and 36.8 thousand employees. It also holds \$1.3 billion in cash and \$2.5 billion in long-term debt, has capital expenditures of \$0.8 billion, a market-to-book equity

[9]Table C1 in Appendix C shows that our results are robust to using different cutoffs. This restriction is not necessary when we use the quantities of product and process innovation output as dependent variables. Table C2 in Appendix C shows that our results are robust to removing this restriction for these two dependent variables.

[10]A comparison with statistics in Table A1 in Appendix A shows that a typical patent of our sample firms closely resembles a typical utility patent issued by the USPTO.

ratio of 4.5, and sales growth of 9.6%. The majority of our sample firms are manufacturing firms (SIC 20-39, 84% of firms) followed by services (SIC 70-89, 10% of firms), while the remaining 6% of firms are evenly populated across the remaining industries. All variables are winsorized at the 1% level before all analyses.

Table 2 further provides summary statistics separately for the treated and control firms computed in 1998. For all characteristics we consider, we find no significant differences between the treated and control firms suggesting that they are similar in terms of observable characteristics prior to the event. In our empirical analysis, we perform further tests which address concerns that omitted variables predicting assignment into the treated or control group also predict our outcome variables.

# V Main Results

To identify the effect of the 1999 U.S.-China bilateral agreement on the process-product innovation mix, we estimate the following difference-in-differences regression

$$y_{i,t} = \alpha_t + \lambda_i + \delta \cdot Agreement_{(t>1999)} \cdot China_i + \beta \cdot X_{i,t-1} + \epsilon_{i,t}, \tag{1}$$

where $i$ and $t$ index firms and years, respectively; $y_{i,t}$ stands for the *Share of process innovations*$_{i,t}$, *Process innovations*$_{i,t}$, or *Product innovations*$_{i,t}$, respectively; $Agreement_{(t>1999)}$ is an indicator variable that takes a value of one in the post-1999 period; $China_i$ is an indicator variable that takes a value of one for firms in the treated group (42% of firms in our sample); $X_{i,t-1}$ are time-varying firm-level control variables lagged by one year; $\alpha_t$ and $\lambda_i$ denote year and firm fixed effects, respectively; and $\epsilon_{i,t}$ is the error term. Coefficient $\delta$ captures the change in the dependent variable at firms with a presence in China as of 1998 following the 1999 U.S.-China bilateral agreement as compared to years before the agreement, relative to firms without such presence.[11]

[11] Variables $Agreement_{(t>1999)}$ and $China_i$ are absorbed by the fixed effects and their coefficients are thus not estimated.

In Columns 1-3 of Table 3, we present estimates of regression (1) with *Share of process innovations*$_{i,t}$ as the dependent variable. The specification in Column 1, which does not include any firm-level control variables, shows that the treated firms lower the share of process innovations relative to control firms post-1999 by 3 percentage points compared to pre-treatment years, which is a 9% reduction relative to the median ratio in the sample. The estimate of coefficient $\delta$ is significant at the 1% level. In Column 2, we additionally control for time-varying firm-level variables, namely, the natural logarithm of firm sales (as a proxy for size) and the market-to-book equity ratio (as a proxy for investment opportunities).[12] In Column 3, we add interacted year and two-digit SIC industry fixed effects to account for any time-varying industry-level omitted variables. We show that including additional controls has little impact on the magnitude and significance of our $\delta$ estimate. This result suggests that our findings are not driven by differences in size, investment opportunities, or industry trends between the two groups of firms.

The reduction in the ratio of process to total innovations we document may be due to less process innovations, more product innovations, or process and product innovations changing at different rates. The agreement arguably had two main effects: it reduced U.S. firms' effective labor cost and it improved the firms' market access to the Chinese market. To the extent that firms have less incentives to invest in R&D to reduce production cost because the agreement reduced U.S. firms' costs from their Chinese operations, we should find that a lower share of process innovations is due to less process innovations. However, it is also possible that a lower share of process innovations is due to more product innovations driven by U.S. firms' needs to introduce new variations of their products as they are gaining a better access to the Chinese market. This prediction stems from theories of industry evolution as pioneered by Utterback and Abernathy (1975).[13]

To distinguish these two possibilities, Columns 4-9 of Table 3 examine the effect of the

[12]Cohen and Klepper (1996) examine the effect of firm size on the allocation of R&D effort between process and product innovation and find evidence that process R&D undertaken by firms rises with firm size.

[13]See also discussion in Klepper (1996) and Mitchell and Skrzypacz (2011).

agreement on the quantities of process and product innovations separately. The dependent variable is *Process innovations*$_{it}$ in Columns 4-6 and *Product innovations*$_{it}$ in Columns 7-9. All columns include firm and year fixed effects and control for the overall intensity of firms' innovation activities using the logarithm of one plus the number of patents in each firm-year. Columns 5-6 and 8-9 additionally control for firm size and the market to book ratio, while Columns 6 and 9 also control for interacted year and two-digit SIC industry fixed effects. We find that the quantity of process innovations decreases after the agreement. The estimate of $\delta$, significant at the 1% level across all specifications, shows a 19% reduction in the number of process claims (Column 6). On the contrary, the quantity of product innovations does not change as $\delta$ estimates are neither statistically nor economically significant. These findings are inconsistent with U.S. firms changing their innovation activities to create new variations of their products for the Chinese market.

Since entry in China is endogenous to the agreement, we define $China_i$ in 1998—the year before the agreement is signed—throughout our baseline analysis. To the extent that all U.S. firms with a presence in China, including those that enter China after 1998, benefit from the agreement, we re-estimate our baseline regressions using a time-varying measure of treatment. To this end, we construct an indicator variable $China_{i,t}$ that takes a value of one if a firm has a subsidiary in China in a given year $t$ according to its 10-K filings (18% of our control firms enter China in 1999 or later), and use it in the interaction with $Agreement_{(t>1999)}$. We report the results in Table C3 in Appendix C for all three dependent variables. The results for the ratio and level of process innovations are similar to those reported in Table 3—negative and significant estimates of $\delta$ are, if anything, slightly bigger in magnitude compared to the baseline estimates.

We perform further robustness tests on our main findings, which we include in Appendix C. Specifically, we show that our results are robust to matching treated and control firms on size and industry as of 1998 and to including in the sample only control firms with subsidiaries in low-wage Asian countries. We also show that our results are robust to using alternative definitions of process and product innovations based on independent claims, as

well as to using patent-level innovation measures.[14]

Our baseline results on the effects of the 1999 U.S.-China bilateral agreement on corporate innovation are consistent with the "access to cheap Chinese labor" explanation.[15] U.S. firms invest in China to take advantage of lower labor cost. The hourly average factory-worker wage in China was \$0.5 in 2000 versus \$16.6 in the U.S. (a ratio of 0.03), while the same ratio is 0.04 in 2005, the final year in our sample.[16] Prior to the agreement, U.S. firms had to work with Chinese partners (e.g., joint-venture counterparts, suppliers, distributors, government). This would lead to hold-up problems, disrupting firms' operations and lowering profits.[17] Hold-up problems are often arising due to contact incompleteness, which is typically the case with international contracts (Rordik, 2000). The agreement expanded the space of applicable contracts, and in particular, allowed U.S. firms to side step, if necessary, working with Chinese partners. The agreement thus increased the share of the profits from Chinese operations accruing to U.S. firms, effectively reducing labor cost. Our results are thus consistent with the view that better access to cheap and abundant Chinese labor reduces the return on investment in process innovations.[18]

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[14]In Appendix C, we also show that our results reported in Table 3 are robust to: i) using different cut-offs to define high-patenting firms (Table C1), ii) dropping the requirement that firms in our sample need to be high-patenting (Table C2), iii) normalizing the quantities of process and product innovations by R&D expenditure or employment (Table C4), and iv) estimating the effect on the quantities of process and product innovations by Negative Binomial count data model (Table C5).

[15]Multinational Monitor comments on the agreement: *"U.S. businesses want the right to exploit its [China's] cheap labor, or at least to import goods made in China with cheap labor."* Porter and Rivkin (2012) asked 10,000 Harvard alumni running businesses what are the main reasons for moving production out of the U.S. 70% of the respondents mention lower wage rates as the main reason for moving existing activities out of the U.S. When the same respondents were asked which are the countries they consider transferring their production to, China was the most common response (42% of the answers).

[16]See Exhibit 1 in a Boston Consulting Group report: *"Why manufacturing will return to the U.S."*.

[17]China is a prominent example of hold-up problems due to the fact that foreign companies have to deal with local counter partners. Antràs (2013) highlights the nature of incomplete contracts in China by citing a Chinese old saying: *"signing a contract is simply a first step in negotiations"*.

[18]Our results may also be interpreted in light of the idea that lower uncertainty over input costs, following the agreement, eliminates firms' option value to delaying changes in their innovation mix (Pindyck, 1993). *"U.S. companies expect to benefit from billions of dollars in new business and an end to years of uncertainty in which they had put off major decisions about investing in China.*

# VI Alternative Explanations

In this section, we examine whether potential confounding effects are driving our results. First, we show that our results are not due to differential pre-treatment trends. Second, we show that our results are not driven by a response of U.S. firms to increasing Chinese import competition, or by improved market access to China. Third, we show that our results are not driven by unobserved economic (e.g., technology or demand) shocks. Fourth, we show that changes in U.S. firms' patenting practices cannot explain our findings.

## VI.1 Pre-treatment trends

In our baseline analysis, the identification comes from the comparison of changes in innovation by firms affected by the agreement (treated firms) with those by firms that are not affected by the agreement (control firms). A possible concern is that the estimated treatment effect could be attributed to differential trends in pre-treatment firm characteristics, because $China_i$ indicator is not randomly assigned. To address this concern, we follow Acemoglu and Finkelstein (2008) and include the interaction term between $China_i$ and an indicator variable that takes a value of one in year 1999 into the specification in Column 3 of Table 3. The coefficient on this interaction term captures possible differential trends in the share of process innovations between the treated and control firms. The result, reported in Column 1 of Table 4, shows that $\delta$ estimate remains unchanged and the estimated coefficient on the new term is positive, small in magnitude, and not statistically significant. This evidence suggests that the treated and control firms do not have different shares of process innovations pre-treatment. We obtain similar results in Columns 3 and 5 of Table 4 when we examine the levels of process and product innovations respectively.

In Columns 2, 4, and 6 of Table 4, we estimate a further augmented version of equation (1) where we interact $China_i$ with an indicator variable for each year $t$. We omit the 1996

*The business relationship has grown rapidly but remains lopsided, partly because of Chinese market restrictions and partly because of the vast discrepancy in wealth between the countries."* (The New York Times, September 2000).

interaction term and thus set 1996 as the baseline year (note that year 1995 is dropped because we lag the control variables). In Column 2, we look at firms' process-product innovation mix and find that no interaction term is significant pre-treatment, while the estimated coefficients for the years following the agreement are all negative and statistically significant at the 5% level. The effect is significant in 2000, the year after the event, its magnitude increases from 2000 to 2001, and it remains fairly stable through 2004. We find similar results in Column 4 for the level of process innovations. This evidence is consistent with findings in the literature that there is no lag between R&D expenditure and patenting, but rather a contemporaneous relationship (Hausman, Hall, and Griliches, 1984; Hall, Griliches, and Hausman, 1986). On the contrary, no coefficient estimate is statistically significant when we look at the level of product innovations in Column 6.

A related concern might be that treated firms' shares of process innovations mean-revert to some firm-specific equilibrium levels post 1999, which is captured by our interaction term. We address this concern in Table C6 in Appendix C. We interact the values of the dependent variables in 1998 (Columns 1, 3, 5) and the value of the number of patents (log-transformed) in 1998 (Columns 2, 4, 6) with the full set of year indicator variables, and add these interaction terms to the Column 3, Table 3 specification. The estimates of $\delta$ are almost identical to our baseline results. We conclude that mean reversion or differential trends in firms' pre-treatment innovation activities cannot explain our findings.

## VI.2 U.S. trade with China

Prior work documents that increases in import competition from low-wage countries impact technical change. A reduction in the relative profitability of making low-tech products due to cheaper imports gives U.S. firms stronger incentives to innovate new goods and climb the quality ladder in order to escape competition. Bernard, Redding, and Schott (2011) show that a reduction of trade costs with a low-wage country leads to a change in the product mix offered by Northern firms toward more high-tech products. Bloom, Draka, and Van Reenen (2015) examine the effect of import competition on innovation and find a positive

effect for firms affected by Chinese imports.[19]

To the extent that our treated and control firms can be differentially affected by import competition, a potential concern could be that a response to Chinese imports in U.S. product markets happening around our event, which arguably lowered trade costs, is driving our results. Contrary to the prediction of the import competition channel that our event would lead to a higher level of product innovations, Table 3 shows that the change in the process-product innovation mix is occurring through a lower level of process innovations.

To further rule our the import competition channel, we add in our baseline specification variable $Agreement_{(t>1999)}$ interacted with variable $IMPORT$, which measures import penetration from China at the 4-digit SIC level as in Bernard, Jensen, and Schott (2006). Columns 1-2 of Table 5 augment the specification in Column 3 of Table 3. In Column 1, $IMPORT$ is defined as the lagged level of import penetration, and, in Column 2, it is defined as the contemporaneous growth rate of import penetration. In both columns, the estimated coefficient on the new interaction term is positive and not statistically significant, while the estimates of $\delta$ remain negative, statistically significant, and are larger in magnitude.

A related argument in the international trade literature is that trade increases market size and induces firms to innovate by reducing the fixed cost of innovation (Krugman, 1980; Grossman and Helpman, 1991, 1992; Lileeva and Trefler, 2010). We thus examine the possibility that U.S. firms with a presence in China export more to China following the agreement due to lower trade costs, which in turn could affect their technological choices. To this end, we add in our baseline specification variable $Agreement_{(t>1999)}$ interacted with variable $EXPORT$, defined as the growth rate of exports from U.S. to China at the 4-digit SIC level as in Schott (2008). In Column 3 of Table 5, we show that the estimated coefficient on this interaction term is not statistically significant, while our effect of the agreement on the treated firms remains. In Column 4, we add in our baseline specification the interaction of variable $Agreement_{(t>1999)}$ with the import penetration growth as well as

[19]See also Amiti and Khandelwal (2013) and Hombert and Matray (2015).

export growth. Again, the effect of the agreement on the treated firms remains, while the two interaction terms are neither economically nor statistically significant. Finally, the last two columns of Table 5 report results from analogous regressions for the levels of process and product innovations. In both cases, we show that our main results continue to hold.[20]

We conclude that our findings do not seem to be due to U.S. firms responding to increasing Chinese imports to their domestic market, or due to improved market access to China following the agreement.

## VI.3 Unobserved economic shocks

We now examine whether unobserved economic shocks, e.g., demand, productivity, or technology shocks, affecting economic conditions in China can be driving our results. To the extent that such shocks, unlike the terms of the agreement, spillover across neighboring geographies, the process-product innovation mix of U.S. firms with subsidiaries in Asian countries other than China would spuriously appear to react to the agreement. To examine this possibility, we augment our baseline specification by including a placebo interaction between variable $Agreement_{(t>1999)}$ and an indicator variable which takes the value of one for firms that have subsidiaries in Asia but not in China ($Asia, NON-China_i$) as reported in their 10-K filings in 1998—a placebo treated group.

In Columns 1-2 of Table 6, we repeat specifications of Columns 2-3 of Table 3 and find that the estimated coefficient on the interaction term with the placebo treated group is neither statistically nor economically significant, while the coefficient on the interaction term with the treated group remains negative, statistically significant, and is larger in magnitude. Columns 3-4 repeat specifications in Columns 5-6 of Table 3 for process innovations and Columns 5-6 repeat specifications in Columns 8-9 of Table 3 for product innovations. We show that the estimates on the placebo treated group interactions are small in terms

[20]It is interesting to note that the level effect of import penetration growth is positive and statistically significant for product innovations (Column 6) and not significant for process innovations (Column 5), which is consistent with the prediction from the trade literature that competition from low-wage countries spurs innovation of new products.

of economic magnitude and not statistically significant, while our baseline results remain unchanged. Thus, regardless of the specification, we are unable to replicate our results for firms having presence in Asia (excluding China). These results address the concern that confounding factors, such as technology or productivity shocks, are driving our results.

## VI.4 Changes in U.S. firms' patenting practices

A possible concern is that trade secrets substitute for process innovations and might be explaining our findings. This is possible, for example, if treated firms expect to transfer more of their production to China following the agreement, which may elevate concerns regarding China's weak intellectual property rights protection. Such concerns may be particularly relevant for process innovations since these innovations are easier to steal or less enforceable (Levin et al., 1987). To address this possibility, we exploit the cross-sectional variation in the degree of enforcement of intellectual property rights across Chinese provinces. In unreported regressions, we find no statistically or economically significant differential effect of the agreement on the share and level of process innovations for firms whose subsidiaries are located in provinces with different intellectual property rights enforcement.[21]

An alternative change in U.S. firms' patenting practices, which may explain our findings, can be related to the possible transfer of some of the firms' R&D centers to China following the agreement. This transfer can be, for example, motivated by positive knowledge spillovers between the production facilities in China and the local R&D centers. Under this scenario, we should observe an increase in (process) patenting activity by treated firms' Chinese subsidiaries following the agreement, which compensates for a decrease in (process) patenting activity by treated firms.

To address this concern, we hand-collect information on the number of patents filed

[21] In this analysis, we follow Ang, Cheng, and Wu (2014) to characterize intellectual property rights enforcement across provinces. Differences in enforcement across provinces has been shown to affect (Chinese) firms' financing and investment (Ang, Cheng, and Wu, 2014), as well as R&D and innovation (Fang, Lerner, and Wu, 2015). We collect information on subsidiaries' locations from the 2001 Survey of Foreign Invested Enterprises (FIEs) conducted by the National Bureau of Statistics in China.

by the treated firms' Chinese subsidiaries over the 1999-2012 period. First, we look for patents applied for at USPTO as U.S. firms tend to patent their most valuable inventions in the U.S. We are unable to find any USPTO patents for the Chinese subsidiaries in our sample. Next, we look for patents applied for at the Chinese State Intellectual Property Office (CSIPO).[22] We find that 55% of the subsidiaries in our sample do not have a patent applied for at CSIPO and the remainder 45% filed at least one patent in China. Conditional on having filed at least one patent, we compute the ratio of the total count of patents filed by the Chinese subsidiary over the total count of patents filed by its U.S. parent firm. The median ratio is 0.003 over the 1999-2012 period. The small magnitude of the ratio suggests that this alternative explanation cannot be driving our results.

# VII Heterogeneous Treatment Effects

In this section, we exploit cross-sectional variation in our sample to highlight the underlying mechanism explaining our findings. First, we show that the negative effect on treated firms is more pronounced when U.S. firms' equity shares in their Chinese subsidiaries are higher vis-à-vis the Chinese shareholders. Second, we find a weaker response to the agreement for U.S. firms that expect to pay higher wage bills in China.

## VII.1 Equity shares in Chinese subsidiaries

We argue that the ability of U.S. firms to extract a higher portion of the profits from their Chinese operations vis-à-vis the Chinese partners increases their benefit from a lower production cost in China. In this view, it is natural to expect that the effect of the agreement on the U.S. firms' process-product innovation mix will be more pronounced in cases where they have higher equity stakes in their Chinese subsidiaries relative to the Chinese partners.

We collect information on equity stakes in Chinese subsidiaries from the 2001 Survey of Foreign Invested Enterprises (FIEs) conducted by the National Bureau of Statistics in

[22] We collect this information from the 'Chinese State Intellectual Property Office Bulk Downloads' page hosted by Google Inc. at http://www.google.com/googlebooks/uspto.html.

China.[23] The survey provides information on the equity shares of U.S. and Chinese parties, which allows us to define variable $EquityShare_i$ as the ratio of the U.S. capital over Chinese capital at registration. The ratio ranges from 0.05 (1st percentile) to 381 (99th percentile) and the median of the ratio is three. Higher ratios mean that U.S. firms can extract relatively higher shares of the profits. We predict a more negative effect of the agreement on the share and level of process innovations for U.S. firms with higher ratios.

In Table 7, we augment our baseline specifications using interaction terms of our treated variable with $EquityShare_i$. To the extent that any omitted variables are uncorrelated with this measure of U.S. firms' equity ratios, the estimates of the coefficients on these interaction terms can be interpreted as triple-difference effects. Columns 1-2 show that the triple-difference effect on the share of process innovations is negative and significant at the 5% or 1% level. The effect is also economically significant. If the ratio of invested capital at registration increases from 1 to 100, the share of process innovations decreases by 4 percentage points (Column 2). Similarly, the triple-difference effect on the level of process innovations in Columns 3-4 is negative and statistically significant at the 5% level. If the ratio of invested capital at registration increases from 1 to 100, the level of process innovations decreases by 9% (Column 4).[24] These results are consistent with the argument that the 1999 U.S.-China bilateral agreement increased the share of the profits U.S. firms capture post-1999 from their Chinese operations, effectively reducing their labor cost and thus changing their process-product innovation mix.

[23]The survey covers FIEs set up by U.S. investors in China that account for 75% of the total number of U.S. FIEs operating in China in 2001 as reported by China Statistical Yearbook 2002 (Du, Lu, and Tao, 2008). The survey is available only in Chinese. We translate it into English and hand-match to our Compustat sample. Our new $China_i$ indicator takes a value of one if, according to the survey, a U.S. firm has set up a subsidiary in China before 1999, and is 0 otherwise. The survey provides information on the date each subsidiary was set up, and thus, to parallel our baseline analysis, we exclude firms which entered China after 1998. In unreported analysis, we find robustness of our baseline results defining our treated $China_i$ dummy using this independent data source.

[24]We obtain similar results if we use instead the ratio of accumulated investment amount in the subsidiary by the U.S. investor over the accumulated investment amount by the Chinese investor.

## VII.2 Wage bill of Chinese subsidiaries

We argue that the effect we are identifying operates through the labor channel. This argument predicts that the treatment effect should be smaller for U.S. firms whose subsidiaries in China expect to pay relatively higher wages. To proxy for the expectation of future wage bills of Chinese subsidiaries, we create an indicator $WageBill_i$ that takes a value of one if the number of workers in the U.S. firm's subsidiary is higher than the sample median and also the minimum wage growth rate in 1998 in the county where the subsidiary is located is higher than the sample median. The information on the number of subsidiaries' workers comes from the 2001 FIEs survey. The survey also provides the location of subsidiaries in China, which allows matching to the minimum wage data at the county level.[25]

In Table 8, we augment our baseline specifications with interaction terms of our treated variable with $WageBill_i$. To the extent that any omitted variables are uncorrelated with this measure of expected future wage bills, the estimates of the coefficients on these interaction terms can be interpreted as triple-difference effects. We find that the triple difference effect on the share of process innovation is positive and statistically significant at the 10% level (Columns 1-2). The triple difference effect on the level of process innovations is also positive and it is statistically significant at the 5% level (Columns 3-4). These results show that U.S. firms who expect wages of their subsidiaries to increase by more cut their process innovation activities by less, which is consistent with our argument that cheap Chinese labor decreases return to investing in labor-saving process innovations.

# VIII An Alternative Experiment

In this section, we turn to an alternative experiment exploiting inter-temporal variation in ownership restrictions on foreign investments across industries imposed by the Chinese government. We show that the removal of ownership restrictions leads to lower share and

[25]The source of minimum wage data is Huang, Loungani, and Wang (2014). The data are originally collected by the Ministry of Human Resources and Social Security in China and official reports of local governments.

level of process innovations, while product innovations do not change. The results from this alternative identification approach confirm our baseline findings.

## VIII.1 Ownership restrictions on foreign investments

Ownership restrictions on foreign investment, typically caps on the share of equity held by foreign investors in Chinese joint-ventures, constitute a major friction that affects how the profits of U.S. firms' Chinese subsidiaries are split between the U.S. vis-à-vis the Chinese partners. The restrictions are formally published in the Catalogue of Industries Guiding Foreign Investment issued jointly by the National Development and Reform Commission (NDRC) and the Ministry of Commerce (MOFCOM), China's governing bodies on economic development and trade and investment policy, respectively, in an effort to regulate foreign investments in China. The 1999 U.S.-China bilateral agreement improved upon doing business in China, nevertheless the ownership restrictions remain throughout 2000s.

The first Catalogue was published in 1995. Since then, the Catalogue was revised five times: in 1997, 2002, 2004, 2007, and 2011. For each industry sector, the Catalogue indicates whether there are restrictions on foreign shareholdings by requiring specific types of foreign investment or by capping the percentage of equity held by foreign investor. Sectors not included in the Catalogue are "permitted", as outlined in the Regulation on Guiding Foreign Investment Direction (State Council Order 346), and no ownership restrictions apply. Sectors included in the Catalogue are "encouraged", "restricted", or "prohibited". "Restricted" sectors are sectors subject to ownership restrictions. "Encouraged" sectors can be either "permitted", and thus no ownership restrictions apply, or "restricted" and are subject to ownership restrictions, but enjoy easier regulatory approval procedures. No investment is allowed in "prohibited" sectors. Despite the several revisions, the structure of the Catalogue remains the same across versions.

We map the industry descriptions from the Catalogue into the industry descriptions of

4-digit NAICS sectoral classification.[26] Next, we group 4-digit NAICS industries into two categories: industries that are not subject to ownership restrictions (permitted or encouraged industries according to the Catalogue) and those that are subject to such restrictions (restricted, encouraged, or prohibited industries according to the Catalogue). We create a dummy variable which takes a value of one if an industry is not subject to ownership restrictions for each year between the issue of the Catalogue and the year of issue of the next Catalogue, and zero if such restrictions are in effect. We end up with time-series information on ownership restrictions for a total of 58 4-digit NAICS industries between 1995, the year the Catalogue was issued for the first time, and 2012, the last year in our sample. Figure 1 presents the percentage of industries in our sample that are not subject to restrictions in each year the Catalogue was issued. Consistent with the fact that China has been opening up its markets to foreign investors, the percentage of industries not subject to restrictions is increasing over time. The biggest change is observed between the 1997 and the 2002 Catalogues, the period around China's entry into WTO.

A change in an industry's status from our "restricted" to "permitted" category has two implications for U.S. firms. The first implication is a direct increase in the share of profits for U.S. firms from their Chinese subsidiaries due to a lower ownership cap on the share of equity. The second implication is an increase in the bargaining power of U.S. firms, which indirectly allows them to extract a higher share of the profits vis-à-vis the Chinese partners. Consider an example of sectors where the Chinese side has to hold (by law) the controlling interest, i.e., more than 50%, of the subsidiary. Similarly to our baseline experiment, lifting this restriction allows U.S. firms to sidestep, if necessary, the Chinese partners, eliminating the potential for hold-up problems and resolving contract incompleteness to their benefit. This implies a reduction in an effective labor cost, which lowers the return on investing in process innovation.[27]

[26]Industry descriptions that do not match with those of the 4-digit NAICS sectors are dropped from the analysis. Assuming instead that the non-matched NAICS sectors are not included in the Catalogue and are thus permitted, does not qualitatively change the results.

[27]This intuition follows from the incomplete-contracting theories of integration in international environments where higher integration for foreign firms entitles them to residual rights of control,

## VIII.2 Effect of restriction removal on innovation mix

To identify changes in U.S. firms' innovation mix due to the ownership restrictions removal, we employ a difference-in-differences regression specifications similar to those used in our baseline experiment. We estimate the relative change in the share and level of process innovations and the level of product innovations at firms with a presence in China, relative to firms without such presence. Specifically, we ask whether the effect of having a presence in China is different following the removal of the restrictions on foreign investors imposed by the Chinese government as compared to years when these restrictions were in effect. We estimate regressions

$$y_{i,t} = \alpha_t + \lambda_i + \delta_1 \cdot Industry_{j,t} \cdot China_{i,t} + \delta_2 \cdot Industry_{j,t} + \delta_3 \cdot China_{i,t} + \beta \cdot X_{i,t-1} + \epsilon_{i,t} \tag{2}$$

where $i$ , $j$, and $t$ index firms, industries, and years, respectively; $y_{i,t}$ stands for the *Share of process innovations*$_{i,t}$, *Process innovations*$_{i,t}$, or *Product innovations*$_{i,t}$, respectively; $Industry_{j,t}$ is a dummy variable that takes a value of one if an industry is not subject to ownership restrictions at year $t$, and is zero otherwise; $China_{i,t}$ is an indicator variable which takes a value of one for firms in our treated group, namely those identified to have presence in China at year $t$;[28] $X_{i,t-1}$ are time-varying firm level control variables lagged by one year; $\alpha_t$ and $\lambda_i$ denote year and firm fixed effects, respectively; and $\epsilon_{i,t}$ is the error term. Coefficient $\delta_1$ captures the within-firm change in the dependent variable at firms operating in industries where the restrictions on foreign investment are lifted, controlling for any concomitant changes in innovation at firms that are still subject to restrictions.

Table 9 presents the results obtained using the sample of intensely patenting firms in 1995-2012 period. Column 1 includes firm fixed effects and year fixed effects, but it does not include any other controls. We find that the share of process innovations in treated

thus improving their ex-post bargaining position and alleviating underinvestment due to hold-up problems (Antràs 2003, 2013).

[28]Since our alternative experiment exploits the variation across industries and over time, we use a time-varying treatment indicator $China_{it}$. In unreported regressions, we repeat our estimation defining treated firms as in our baseline analysis and find similar results.

firms decreases by 5 percentage points following the ownership restrictions removal, as compared to control firms. The estimate of $\delta_1$ is significant at the 1% level. In Column 2, we additionally control for firm sales and market to book ratio to control for size and investment opportunities at the firm level. In Column 3, we additionally control for interacted industry and year fixed effects to account for any time-varying industry-level unobservables. The estimate of $\delta_1$ remains statistically significant at the 1% or 5% level, and its magnitude is practically unchanged.[29] In Columns 4-9 of Table 9, we present the results on the levels of process and product innovations. Process innovations are lower by 25% (Column 6) and the estimated effect is statistically significant at the 1% or 5% level. On the contrary, the effect on product innovations is small in magnitude and is never statistically significant. These results, obtained using an alternative identification approach, further support our findings that greater ability of U.S. firms to benefit from cheaper Chinese labor lead to less process innovations.

# IX Conclusion

China's transformation into private-sector-led economy and its integration into the global economy have been among the most dramatic economic developments of recent decades. The literature has focused on studying the effects of rapidly growing trade with China on the developed economies. However, China is also one of the largest recipients of foreign investment ($1.9 trillion over the 1995-2012 period according to the World Bank) by multinationals that want to tap Chinese labor market. We thus examine how the availability of abundant, cheap Chinese labor affects the direction of technological change.

To answer this question, we construct a novel firm-level data set on process and product innovations using text-based analysis of patents filed in the U.S. We show that the innovation mix shifted towards less process innovation for U.S. firms invested in China following the 1999 U.S.-China bilateral agreement. The agreement increased the share of

[29]Standard errors are clustered at the 4-digit NAICS industry level. In unreported regressions we find that our results are robust to clustering at the firm level.

profits accruing to U.S. firms vis-à-vis the Chinese partners, lowering U.S. firms' effective labor costs. When Chinese labor is more attractive due to the agreement, the return on investing in process innovation (its substitute) relatively decreases, making process innovation less attractive. We replicate our results in a different setting—using the inter-temporal variation in foreign ownership restrictions across industries in 1995-2012.

The 1999 U.S.-China bilateral agreement, as well as agreements signed with other countries, was certainly an important step toward creating one world economic system. Currently, an ongoing discussion is taking place on a new trade agreement between the United States and the European Union. Our results highlight that such agreements can be key determinants of technology choices of firms, allowing them to more efficiently organize their innovation activities and shift technological frontiers.

# References


[1] Acemoglu, D., 2007, "Equilibrium Bias of Technology", *Econometrica*, 75, 1371-1409.

[2] Acemoglu, D., 2010, "When Does Labor Scarcity Encourage Innovation?", *Journal of Political Economy*, 118, 1037-1078.

[3] Acemoglu, D., and A. Finkelstein, 2008, "Input and Technology Choices in Regulated Industries: Evidence from the Health Care Sector", *Journal of Political Economy*, 116, 837-880.

[4] Acemoglu, D., D. Autor, D. Dorn, and G. H. Hanson, 2014, "Import Competition and the Great U.S. Employment Sag of the 2000s", *Journal of Labor Economics*, forthcoming.

[5] Amiti, M., and A. K. Khandelwal, 2013, "Import Competition and Quality Upgrading", *Review of Economics and Statistics*, 95, 476-490.

[6] Ang, J., Y. Cheng, and C. Wu, 2014, "Does Enforcement of Intellectual Property Rights Matter in China? Evidence from Financing and Investment Choices in the High Tech Industry", *Review of Economics and Statistics*, 96, 332-348.

[7] Antràs, P., 2003, "Firms, Contracts, and Trade Structure", *Quarterly Journal of Economics*, 118, 1375-1418.

[8] Antràs, P., 2005, "Incomplete Contracts and the Product Cycle", *American Economic Review*, 95, 1054-1073.

[9] Antràs, P., 2013, "Grossman–Hart (1986) Goes Global: Incomplete Contracts, Property Rights, and the International Organization of Production", *The Journal of Law, Economics, and Organization*, 0, 1-58.

[10] Autor, D. H., D. Dorn, and G. H. Hanson, 2013, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States", *American Economic Review*, 103, 2121-2168.

[11] Autor, D., D. Dorn, and G. H. Hanson, 2016, "The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade", Working Paper.

[12] Bena, J., A. M. Ferreira, P. Matos, and P. Pires, 2016, "Are Foreign Investors Locusts? The Long-Term Effects of Foreign Institutional Ownership", University of Virginia – Darden School of Business, Working paper.

[13] Bernard, A. B., J.B. Jensen, and P. Schott, 2006, "Survival of the Best Fit: Low Wage Competition and the (Uneven) Growth of US Manufacturing Plants", *Journal of International Economics*, 68, 219-237.

[14] Bernard, A. B., S. J. Redding, and P. Schott, 2011, "Multi-Product Firms and Trade Liberalization", *Quarterly Journal of Economics*, 126, 1271-1318.

[15] Bloom, N., M. Draka, and J. Van Reenen, 2015, "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity", *Review of Economic Studies*, forthcoming.

[16] Caselli, F., and W. J. Coleman II, 2006, "The World Technology Frontier", *American Economic Review*, 96, 499-522.

[17] Ciccone, A., and E. Papaioannou, 2009, "Human Capital, the Structure of Production, and Growth", *Review of Economics and Statistics*, 91, 66-82.

[18] Cohen, W. M., and S. Klepper, 1996, "Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D", *Review of Economics and Statistics*, 78, 232-243.

[19] Desai, M. A., C. F Foley, and J. R. Hines, 2004, "The Costs of Shared Ownership: Evidence from International Joint Ventures", *Journal of Financial Economics*, 73, 324-374.

[20] Devereaux, C., and R. Lawrence, 2004, "The Eagle and the Dragon: The November 1999 US-China Bilateral Agreement and the Battle Over PNTR", Harvard Case Study, HKS476.

[21] Du, J., Y. Lu, and Z. Tao, 2015, "Economic Institutions and FDI Location Choice: Evidence from US Multinationals in China", *Journal of Comparative Economics*, 36, 412-429.

[22] Eswaran, M., and N. Gallini, 1996, "Patent Policy and the Direction of Technological Change", *The RAND Journal of Economics*, 27, 722-746.

[23] Fang, L. H., J. Lerner, and C. Wu, 2015, "Intellectual Property Rights Protection, Ownership, and Innovation: Evidence from China", Working Paper.

[24] Griliches, Z., 1990, "Patent Statistics as Economic Indicators: A Survey", *Journal of Economic Literature*, 28, 1661-1707.

[25] Grossman, G., and E. Helpman, 1991, "Quality Ladders and Product Cycles", *Quarterly Journal of Economics*, 106, 557-586.

[26] Grossman, G., and E. Helpman, 1992, "Innovation and Growth in the Global Economy", Cambridge: MIT Press.

[27] Habakkuk, H. J., 1962, "American and British Technology in the Nineteenth Century: Search for Labor Saving Inventions", Cambridge, England: Cambridge University Press.

[28] Hall, B. H., Z. Griliches, and J. Hausman, 1986, "Patents and R&D: Is there a Lag?", *International Economic Review*, 27, 265-283.

[29] Hanlon, W., 2015, "Necessity is the Mother of Invention: Input Supplies and Directed Technical Change", *Econometrica*, 83, 67-100.

[30] Hausman, J., B., H., Hall, and Z. Griliches, 1984, "Econometric Models for Count Data with an Application to the Patens-R&D Relationship", *Econometrica*, 52, 909-938.

[31] Hicks, J., 1932, "The Theory of Wages", London: Macmillan.

[32] Hombert, J., and A. Matray, 2015, "Can Innovation Help U.S. Manufacturing Firms Escape Import Competition from China?", Working Paper.

[33] Huang, Y., P. Loungani, and G. Wang, 2015, "Minimum Wages and Firm Employment: Evidence from China", IMF Working Paper.

[34] Klepper, S., 1996, "Association Entry, Exit, Growth, and Innovation over the Product Life Cycle", *American Economic Review*, 86, 562-583.

[35] Krugman, P., 1980, "Scale Economies, Product Differentiation, and the Pattern of Trade", *American Economic Review*, 70, 950-959.

[36] Levin, R. C., A. K. Klevorick, and R. R. Nelson, 1987, "Appropriating the Returns from Industrial R&D", *Brookings Papers on Economic Activity*, 783-820.

[37] Lileeva, A., and D. Trefler, 2010, "Improved Access to Foreign Markets Raises Plant-Level Productivity...for Some Plants", *Quarterly Journal of Economics*, 125, 1051-1099.

[38] Link, A. N., 1982, "A Disaggregated Analysis of Industrial R&D: Product versus Process Innovation", in Devendra Sahal (ed.), The Transfer and Utilization of Technical Knowledge (Lexington, MA: Lexington Books).

[39] Midler, P., 2009, "Poorly Made in China", Hoboken, NJ: John Wiley & Sons, Inc.

[40] Mitchell, M. and A. Skrzypacz, 2011, "A Theory of Market Pioneers", Working Paper.

[41] Moran, T. H., 2001, "Parental Supervision: The New Paradigm for Foreign Direct Investment and Development", Institute for International Economics, Washington, D.C.

[42] Nelson, R. R., and E. S. Phelps, 1966, "Investment in Humans, Technical Diffusion, and Economic Growth", *American Economic Review*, 56, 69-75.

[43] Newell, R., A. Jaffe, and R. Stavins, 1999, "The Induced Innovation Hypothesis and Energy-Saving Technological Change", *Quarterly Journal of Economics*, 114, 941-975.

[44] Pierce, J. R., and P. K. Schott, 2015, "The Surprisingly Swift Decline of U.S. Manufacturing Employment", NBER Working Paper Series.

[45] Pindyck, R. S., 1993, "Investments of Uncertain Costs", *Journal of Financial Economics*, 31, 53-76.

[46] Porter, M. E., and J. W. Rivkin, 2012, "Prosperity at Risk: Findings of Harvard Business School's Survey on U.S. Competitivenes", Report.

[47] Rodrik, D., 2000, "How Far Will International Economic Integration Go?", *Journal of Economic Perspectives*, 14, 177-186.

[48] Scherer, F. M., 1982, "Inter-industry Technology Flows in the United States", *Research Policy*, 11, 227-245.

[49] Scherer, F. M., 1984, "Using Linked Patent and R&D Data to Measure Interindustry Technology Flows", in Zvi Griliches (ed.), *R&D, Patents, and Productivity* (Chicago: University of Chicago Press for the National Bureau of Economic Research).

[50] Schott, P., 2008, "The Relative Sophistication of Chinese Exports", *Economic Policy*, 53, 5-49.

[51] Utterback, J. M., and W. J. Abernathy, 1975, "The Induced Innovation Hypothesis and Energy-Saving Technological Change", *OMEGA*, 3, 639-656.

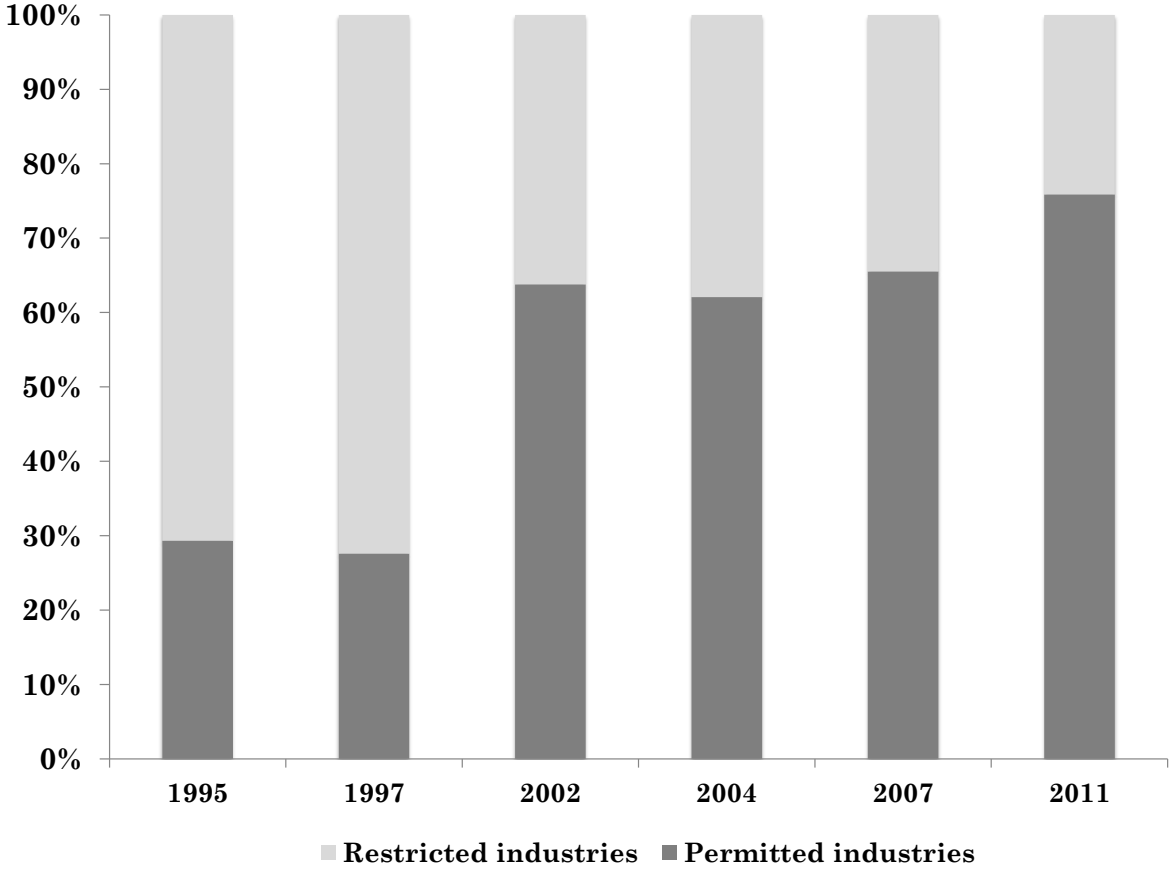


**Figure 1. Breakdown of "Permitted" and "Restricted" industries for each Foreign Investment Catalogue**

This figure shows the percentage of industries where investment is subject to ownership restrictions (light grey) and those where investment is permitted without ownership restrictions (dark grey). The information is provided by the Catalogue of Industries Guiding Foreign Investment issued jointly by the National Development and Reform Commission ("NDRC") and the Ministry of Commerce ("MOFCOM") of China. The Foreign Investment Catalogue was initially issued in 1995 and was revised five times since then: in 1997, 2002, 2004, 2007, 2011.

## Table 1: Process and product innovations

This table reports summary statistics on patent claims for the set of patents assigned to Compustat firms in our baseline sample used in Table 3. There are 362,534 patents over the period 1995-2004. Patent claims define – in technical terms – the scope of protection conferred by a patent, and thus define what subject matter the patent protects. A process claim refers to innovations that reduce production costs, while product claims refer to new goods. An independent claim stands on its own, while a dependent claim, in contrast, only has meaning when combined with a claim it refers to.

| | Mean | Standard Deviation | 25th Percentile | 50th Percentile | 75th Percentile |
|---|---|---|---|---|---|
| Number of Claims | 19.60 | 14.20 | 10 | 17 | 25 |
| Number of Process Claims | 7.36 | 9.73 | 0 | 5 | 11 |
| Number of Product Claims | 12.30 | 11.70 | 4 | 10 | 18 |
| Number of Independent Claims | 3.44 | 2.67 | 2 | 3 | 4 |
| Number of Dependent Claims | 16.20 | 13.00 | 8 | 14 | 21 |

## Table 2: Summary statistics

This table reports summary statistics for key financial variables for the full sample, and for treated and control firms, as measured in 1998, the year prior to the US-China bilateral agreement. Treated firms are defined as intensely patenting firms which have a subsidiary in China as of 1998, and control firms are intensely patenting firms without such presence. Column 1 reports means, Column 2 reports standard deviations for the full sample. 25th, 50th and 75th percentiles are reported in Columns 3-5. Columns 6 and 7 present means and standard errors, respectively, for treated and control firms, as measured in 1998. Column 8 reports p-values from the t-test for the difference in means between treated and control firms.

| | Mean | Standard Deviation | 25th Percentile | 50th Percentile | 75th Percentile | | Mean | Standard Errors | p-value of Difference |
|---|---|---|---|---|---|---|---|---|---|
| | All firm-years (N=2,399) | | | | | | In Year 1998 | | |
| Share of Process Innovations | 0.337 | 0.172 | 0.216 | 0.332 | 0.444 | treated | 0.328 | (0.017) | 0.52 |
| | | | | | | control | 0.343 | (0.017) | |
| Share of Process Innovations_Patent | 0.330 | 0.212 | 0.175 | 0.301 | 0.458 | treated | 0.301 | (0.020) | 0.23 |
| | | | | | | control | 0.336 | (0.021) | |
| Sales (mil. $) | 10,402 | 23,190 | 864 | 2,409 | 9,293 | treated | 10,220 | (1,830) | 0.63 |
| | | | | | | control | 8,860 | (1,967) | |
| Assets (mil. $) | 13,607 | 34,926 | 1,014 | 2,836 | 10,529 | treated | 11,594 | (2,671) | 0.98 |
| | | | | | | control | 11,464 | (2,993) | |
| Employees (thous.) | 36.79 | 62.44 | 4.02 | 11.65 | 40.29 | treated | 33.01 | (5.78) | 0.33 |
| | | | | | | control | 40.94 | (5.49) | |
| Cash (mil. $) | 1,258 | 2,869 | 80 | 275 | 955 | treated | 791 | (88) | 0.57 |
| | | | | | | control | 857 | (114) | |
| Long-term Debt (mil. $) | 2,483 | 7,656 | 33 | 417 | 1,606 | treated | 2,000 | (548) | 0.80 |
| | | | | | | control | 2,236 | (679) | |
| Ebitda (mil. $) | 1,841 | 4,207 | 131 | 396 | 1,536 | treated | 1,937 | (300) | 0.39 |
| | | | | | | control | 1,501 | (373) | |
| Capex (mil. $) | 783 | 2,253 | 47 | 148 | 519 | treated | 781 | (183) | 0.99 |
| | | | | | | control | 785 | (213) | |
| Market to Book | 4.49 | 5.19 | 2.02 | 3.14 | 5.23 | treated | 5.91 | (0.63) | 0.31 |
| | | | | | | control | 5.04 | (0.58) | |
| Sales Growth (%) | 9.57 | 23.97 | -0.71 | 8.27 | 18.19 | treated | 6.31 | (1.61) | 0.23 |
| | | | | | | control | 9.98 | (2.34) | |

## Table 3: U.S.-China bilateral agreement and process and product innovations

This table reports results of OLS regressions of the share of process innovations (Columns 1-3), and level of process (Columns 4-6) and product (Columns 7-9) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. Process and product innovations are log-transformed. $China_i$ is a dummy which takes the value of 1 if a U.S. firm has a subsidiary in China in 1998, and is 0 otherwise. The sample period is 1995-2004. Market to Book is defined as the ratio of the market value of equity plus book value of debt over the book value of debt plus equity, log-transformed and lagged by one year. Sales is log-transformed and lagged by one year. Patents is one plus the total number of patents at a given firm-year and is log-transformed. All regressions include firm and year fixed effects. Columns 3, 6, and 9 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | | Process Innovations | | | Product Innovations | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0301 | -0.0339 | -0.0321 | -0.182 | -0.185 | -0.187 | -0.0165 | -0.0061 | -0.0221 |
| | (0.0120)*** | (0.0121)*** | (0.0125)*** | (0.0566)*** | (0.0571)*** | (0.0584)*** | (0.0368) | (0.0364) | (0.0388) |
| Sales | | -0.0152 | -0.0176 | | -0.0483 | -0.0454 | | 0.0387 | 0.0386 |
| | | (0.0108) | (0.0110) | | (0.0399) | (0.0415) | | (0.0356) | (0.0356) |
| Market to Book | | 0.0043 | -0.0002 | | 0.0589 | 0.0403 | | 0.0399 | 0.0397 |
| | | (0.0060) | (0.0060) | | (0.0263)** | (0.0282) | | (0.0188)** | (0.0187)** |
| Patents | | | | 1.157 | 1.130 | 1.118 | 1.106 | 1.095 | 1.103 |
| | | | | (0.0272)*** | (0.0320)*** | (0.0314)*** | (0.0207)*** | (0.0226)*** | (0.0249)*** |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | | Yes | Yes | | Yes | Yes | |
| Industry×Year FE | | | Yes | | | Yes | | | Yes |
| $R^2$ | 0.72 | 0.76 | 0.80 | 0.93 | 0.94 | 0.95 | 0.96 | 0.96 | 0.97 |
| Obs. | 2,399 | 2,051 | 2,051 | 2,399 | 2,051 | 2,051 | 2,399 | 2,051 | 2,051 |

## Table 4: Pre-treatment trends

This table reports results of OLS regressions of the share of process innovations (Columns 1-2), and level of process (Columns 3-4) and product (Columns 5-6) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. Process and product innovations are log-transformed. $China_i$ is a dummy which takes the value of 1 if a U.S. firm has a subsidiary in China in 1998, and is 0 otherwise. $d_t$ is an indicator variable for yeat $t$. The sample period is 1995-2004. Firm-level controls include Market to Book ratio and firm sales in all columns and number of patents in Columns 3-6. Controls are defined as in Table 3. All regressions include firm and interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | Process Innovations | | Product Innovations | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0302 | | -0.200 | | -0.0378 | |
| | (0.0133)** | | (0.0608)*** | | (0.0445) | |
| $d_{1997} \cdot China_i$ | | -0.0091 | | -0.0343 | | 0.0692 |
| | | (0.0147) | | (0.0783) | | (0.0543) |
| $d_{1998} \cdot China_i$ | | -0.0250 | | -0.140 | | 0.0821 |
| | | (0.0186) | | (0.103) | | (0.0618) |
| $d_{1999} \cdot China_i$ | 0.0072 | -0.0045 | -0.0485 | -0.109 | -0.0583 | -0.0065 |
| | (0.0170) | (0.0198) | (0.0867) | (0.106) | (0.0633) | (0.0751) |
| $d_{2000} \cdot China_i$ | | -0.0360 | | -0.178 | | 0.0189 |
| | | (0.0177)** | | (0.0982)* | | (0.0658) |
| $d_{2001} \cdot China_i$ | | -0.0421 | | -0.284 | | 0.0203 |
| | | (0.0196)** | | (0.0899)*** | | (0.0646) |
| $d_{2002} \cdot China_i$ | | -0.0407 | | -0.213 | | 0.0079 |
| | | (0.0202)** | | (0.104)** | | (0.0706) |
| $d_{2003} \cdot China_i$ | | -0.0423 | | -0.328 | | 0.0015 |
| | | (0.0210)** | | (0.102)*** | | (0.0711) |
| $d_{2004} \cdot China_i$ | | -0.0489 | | -0.304 | | 0.0201 |
| | | (0.0218)** | | (0.114)*** | | (0.0724) |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry×Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.80 | 0.80 | 0.95 | 0.95 | 0.97 | 0.97 |
| Obs. | 2,051 | 2,051 | 2,051 | 2,051 | 2,051 | 2,051 |

## Table 5: U.S. trade with China

This table reports results of OLS regressions of the share of process innovations (Columns 1-4), and level of process (Column 5) and product (Column 6) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. $IMPORT$ is measured as the level of lagged Chinese import penetration in the U.S. in Column 1, and as the growth rate of Chinese import penetration in Columns 2 and 4-6. $EXPORT$ is measured as the export growth rate of the U.S. to China. $IMPORT$ is measured as in Bernard, Jensen, and Schott (2006) and is available for manufacturing 4-digit SIC industries. $EXPORT$ is computed based on U.S. exports to China available for 4-digit SIC manufacturing industries from Schott (2008). The sample period is 1995-2004. Firm-level controls include Market to Book ratio and firm sales in all columns and number of patents in Columns 5-6. Controls are defined as in Table 3. All regressions include firm and interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | | | Process Innovations | Product Innovations |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0366 | -0.0369 | -0.0363 | -0.0364 | -0.235 | -0.0307 |
| | (0.0161)** | (0.0163)** | (0.0164)** | (0.0163)** | (0.0813)*** | (0.0449) |
| $Agreement_{(t>1999)} \cdot IMPORT$ | 0.00669 | 0.00573 | | 0.00547 | 0.0186 | 0.00678 |
| | (0.0497) | (0.00841) | | (0.00847) | (0.0475) | (0.0224) |
| $Agreement_{(t>1999)} \cdot EXPORT$ | | | -0.0117 | -0.0099 | -0.0267 | 0.0332 |
| | | | (0.0103) | (0.0105) | (0.0436) | (0.0229) |
| $IMPORT$ | -0.176 | -0.0007 | | -0.0007 | -0.0006 | 0.0025 |
| | (0.182) | (0.0003)** | | (0.0003)** | (0.0007) | (0.0007)*** |
| $EXPORT$ | | | 0.00216 | 0.0014 | -0.00001 | -0.0082 |
| | | | (0.0036) | (0.0039) | (0.0014) | (0.0113) |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry×Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.75 | 0.75 | 0.75 | 0.75 | 0.94 | 0.97 |
| Obs. | 1,346 | 1,325 | 1,325 | 1,325 | 1,325 | 1,325 |

## Table 6: Unobserved economic shocks

This table reports results of OLS regressions of the share of process innovations (Columns 1-2), and level of process (Columns 3-4) and product (Columns 5-6) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. $Asia, NON-China_i$ is an indicator which takes a value of 1 if a US firm has a subsidiary in Asia, but not China, and 0 otherwise. The sample period is 1995-2004. Firm-level controls include Market to Book ratio and firm sales in all columns and number of patents in Columns 3-6. Controls are defined as in Table 3. All regressions include firm and year fixed effects. Columns 2, 4 and 6 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | Process Innovations | | Product Innovations | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0308 | -0.0344 | -0.198 | -0.209 | -0.0207 | -0.0227 |
| | (0.0183)* | (0.0189)* | (0.0715)*** | (0.0756)*** | (0.0511) | (0.0563) |
| $Agreement_{(t>1999)} \cdot Asia, NON-China_i$ | 0.0044 | -0.0033 | -0.0193 | -0.0315 | -0.0210 | -0.0008 |
| | (0.0192) | (0.0189) | (0.0786) | (0.0854) | (0.0537) | (0.0618) |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes | | Yes |
| $R^2$ | 0.76 | 0.80 | 0.94 | 0.95 | 0.96 | 0.97 |
| Obs. | 2,051 | 2,051 | 2,051 | 2,051 | 2,051 | 2,051 |

Table 7: Cross-sectional heterogeneity: Equity shares in Chinese subsidiaries

This table reports results of OLS regressions of the share of process innovations (Columns 1-2) and level of process innovations (Columns 3-4) on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. $China_i$ is defined based on the 2001 survey of foreign invested enterprises conducted by the National Bureau of Statistics in China, which we linked to Compustat. $EquityRatio_i$ is defined as the ratio of US capital at registration over Chinese capital at registration for the U.S. subsidiary in China. The sample period is 1995-2004. Firm-level controls include Market to Book ratio and firm sales in all columns and number of patents in Columns 3-4. Controls are defined as in Table 3. All regressions include firm and year fixed effects. Columns 2, and 4 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | Process Innovations | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0155 | -0.0033 | -0.0779 | -0.0461 |
| | (0.0134) | (0.0144) | (0.0601) | (0.0646) |
| $Agreement_{(t>1999)} \cdot China_i \cdot EquityRatio_i$ | -0.00041 | -0.00039 | -0.00123 | -0.00094 |
| | (0.00016)** | (0.00013)*** | (0.00049)** | (0.00048)** |
| Firm-level Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes |
| $R^2$ | 0.78 | 0.82 | 0.94 | 0.95 |
| Obs. | 1,766 | 1,766 | 1,766 | 1,766 |

Table 8: Cross-sectional heterogeneity: Wage bill of Chinese subsidiaries

This table reports results of OLS regressions of the share of process innovations (Columns 1-2) and level of process innovations (Columns 3-4) on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. $China_i$ is defined based on the 2001 survey of foreign invested enterprises conducted by the National Bureau of Statistics in China, which we linked to Compustat. $Wagebill_i$ is an indicator which is 1 if the number of workers at the US subsidiary in China is higher than the sample median and, at the same time, the growth rate of the subsidiary's county minimum wage in 1998 is higher than the sample median, and is 0 otherwise. The sample period is 1995-2004. Firm-level controls include Market to Book ratio and firm sales in all columns and number of patents in Columns 3-4. Controls are defined as in Table 3. All regressions include firm and year fixed effects. Columns 2, and 4 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | Process Innovations | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0471 | -0.0353 | -0.255 | -0.217 |
| | (0.0149)*** | (0.0168)** | (0.0734)*** | (0.0820)*** |
| $Agreement_{(t>1999)} \cdot China_i \cdot WageBill_i$ | 0.0348 | 0.0393 | 0.218 | 0.208 |
| | (0.0213)* | (0.0233)* | (0.106)** | (0.0944)** |
| Firm-level Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes |
| $R^2$ | 0.77 | 0.81 | 0.93 | 0.94 |
| Obs. | 1,529 | 1,529 | 1,529 | 1,529 |

## Table 9: Foreign investment catalogues and process and product innovations

This table reports results of OLS regressions of the share of process innovations (Columns 1-3), and level of process (Columns 4-6) and product (Columns 7-9) innovations on firms operating in industries where ownership restrictions are lifted as compared to a set of control firms. $Industry_{jt}$ takes a value of 1 if an industry is not subject to ownership restrictions at a given year, and 0 otherwise, and it is defined at the 4-digit NAICS level. $China_{it}$ takes a value of 1 if a U.S. firm has a subsidiary in China in year $t$, and is 0 otherwise. The sample period is 1995-2012. Firm-level controls include Market to Book and firm sales in Columns 2-3, 5-6 and 8-9. Firm-level controls additionally control for patents in Columns 4-9. Controls are defined as in Table 3. All regressions include firm and year fixed effects. Columns 3, 6 and 9 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the 4-digit NAICS-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | | Process Innovations | | | Product Innovations | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $Industry_{jt} \cdot China_{it}$ | -0.0504 | -0.0611 | -0.0516 | -0.234 | -0.257 | -0.252 | 0.0332 | 0.0730 | 0.0436 |
| | (0.0184)*** | (0.0188)*** | (0.0221)** | (0.0906)*** | (0.0983)*** | (0.113)** | (0.0570) | (0.0639) | (0.0599) |
| $China_{it}$ | 0.0468 | 0.0558 | 0.0483 | 0.297 | 0.306 | 0.250 | 0.0093 | -0.0464 | -0.0667 |
| | (0.0129)*** | (0.0140)*** | (0.0139)*** | (0.0780)*** | (0.0948)*** | (0.101)** | (0.0454) | (0.0576) | (0.0609) |
| $Industry_{jt}$ | 0.0321 | 0.0352 | 0.0062 | 0.0575 | 0.106 | 0.0725 | -0.103 | -0.0793 | 0.0167 |
| | (0.0144)** | (0.0133)** | (0.0173) | (0.0749) | (0.0702) | (0.119) | (0.0621) | (0.0648) | (0.0596) |
| Firm-level controls | | Yes | Yes | | Yes | Yes | | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | | Yes | Yes | | Yes | Yes | |
| Industry×Year FE | | | Yes | | | Yes | | | Yes |
| $R^2$ | 0.58 | 0.61 | 0.64 | 0.88 | 0.89 | 0.90 | 0.89 | 0.90 | 0.91 |
| Obs. | 3,855 | 3,400 | 3,400 | 3,855 | 3,400 | 3,400 | 3,855 | 3,400 | 3,400 |

# Appendix A: Process and Product Innovations

***Procedure to Distinguish Claim Types***

Patent grant publication documents are structured using Extensible Markup Language (XML), a markup language that defines a set of rules for encoding documents in a format that is both human-readable and machine-readable. Within a patent grant publication document, claims are numbered sequentially, with the first claim typically being the broadest and the most important one. Claims are of two basic types: product or process. Claims are written in a very legalistic and stilted way, which allows us to apply text analysis techniques to clearly determine the claim type. Claims that refer to process innovations begin with "A method for" or "A process for" (or minor variations of these two strings) followed by a verb (typically in gerund form), which directs to actions that are to take place as part of the process. We denote claims with such beginnings as process claims, while we denote the residual as product claims. Claims are also either independent or dependent. An independent claim stands on its own, while a dependent claim has meaning only when combined with a claim it refers to. We machine-read the text of each claim in order to identify references the claim makes to other claims of the same patent. We denote claims that contain such references as dependent claims, while we denote the residual as independent claims.

For example, USPTO patent grant document US 8317964 B2 titled "Method of manufacturing a vehicle" applied for on January 11, 2007 by Ford Motor Company has 11 process claims to protect a method of manufacturing a vehicle (Figure A1). The wording of claim 1 begins: "1. A method of manufacturing a vehicle comprising...". The wording of claim 2 begins: "2. The method of claim 1 wherein the step of assembling the upper portion further comprises...". We code claims 1 and 2 to be process claims, wherein claim 1 is an independent and claim 2 is a dependent claim. On the other hand, USPTO patent grant document US 7535468 B2 titled "Integrated sensing display" applied for on June 21, 2004 by Apple Inc. has 22 product claims to protect the invention of an integrated sensing display (Figure A2). The wording of claim 1 begins: "1. A device comprising a display

panel...". The wording of claim 2 begins: "2. The device of claim 1, wherein the image elements are located in a ...". We code claims 1 and 2 to be product claims, wherein claim 1 is an independent claim and claim 2 is a dependent claim.

***Summary Statistics***

Table A1 reports summary statistics on claim types per patent. Panel A is based on the universe of 4,233,476 utility patents applied for at USPTO by firms with application dates between January 1976 and December 2012. On average, a patent has 15.2 claims, of which 4.6 are process, 10.7 are product, 2.7 are independent, and 12.5 are dependent. In this sample, process claims are 30% of total claims, and product claims are 70% of total claims. When we look at the patent decomposition, there are 15.4% process patents, 56% product patents, 11.3% process-apparatus patents, and 17.4% product-method patents. Panel B is based on 1,855,328 utility patents applied for at USPTO by firms matched to Compustat with application dates between January 1976 and December 2012. The innovation mix of Compustat firms is very similar to that of the patent universe. Specifically, on average, a patent has 16.0 claims, of which 5.3 are process, 10.7 are product, 2.9 are independent, and 13.1 are dependent. In this sample, process claims are 33% of total claims, and product claims are 67% of total claims. When we look at the patent decomposition, there are 16.7% process patents, 49% product patents, 14.5% process-apparatus patents, and 20.1% product-method patents.

***External Validity: Survey Evidence & Some Illustrative Correlations***

Since we are the first to decompose innovations into new products and processes using patent data for a broad sample of firms, we provide several validity checks on main measures used in our analyses. First, we compare the process-product innovation mix computed using our data with that reported by other sources. The 'Business Research and Development and Innovation Survey' in the U.S., conducted by the National Science Foundation (NSF), reports the number of R&D performing firms that introduced new products or processes every year since 2006. On average, 42% of firms performing R&D over the 2006-2011 period, and 44% of firms with R&D activity over $100 million, report that they perform

process innovation. Comparably, using our data, we find that 46% of Compustat firms patented process innovations over the same period. We also find that, over the same period on average, 39% of patented innovations are process innovations, albeit there is no question in the NSF survey that would allow us to make a direct comparison.[30] Analogous statistics to those available in the NSF survey are also provided by the 'European Firms in Global Economy: internal policies for external competitiveness' (EFIGE) survey performed in 2010 in 8 European countries. Table A2 in Appendix A shows that the percentage of firms active in process innovation ranges from 40 to 51 in these countries. Overall, both surveys confirm our finding that about 45% of R&D-active firms engage in process innovation.

Next, we qualitatively validate our measures relying on the findings of the job polarization literature. There are two prominent explanations in this literature for the displacement of the middle-skilled jobs that we observe in the aggregate data. The first explanation is that technological progress allows firms to replace expensive labor that performs routine tasks with technology (Autor, Levy, and Murnane 2003; Acemoglu and Autor, 2011). To the extent that process innovations are aimed at reducing production cost (Scherer 1982, 1984; Link 1982; Cohen and Klepper, 1996; Eswaran and Gallini, 1996), we predict that process innovations displace routine labor tasks that can be more easily performed by technology. Due to this displacement, we should observe a negative correlation between process innovations and the subsequent change in the labor routine tasks intensity. The second explanation is that the globalization of labor markets allows firms to offshore part of their production to low-wage countries (Blinder 2009; Blinder and Krueger, 2013). This implies that process innovations should be less beneficial if labor tasks are easily offshorable. We show evidence consistent with both predictions in Table A3 and in Table A4.

We classify labor routine tasks intensity at the industry-year level. We use the Occupational Employment Statistics (OES), provided by the Bureau of Labor Statistics, to obtain information on total employment by occupation for each 4-digit NAICS industry over the 2002-2012 period. Using the classification of tasks' routine intensity in Autor, Levy, and

[30]Estimates from earlier studies of the average process share in the manufacturing sector in the 1980s ranges between 25% to 30%. See Cohen and Klepper (1996) for a more detailed discussion.

Murnane (2003) and Standard Occupational Classification (SOC) codes, we construct the average routine intensity of occupations in a given 4-digit NAICS industry-year, weighted by total employment for each occupation in a given industry-year.[31] Consistent with our intuition, Table A3 shows that higher shares and levels of process innovations are negatively associated with the change in an industry's labor routine tasks intensity over the subsequent 5 years.

We are also able to characterize the offshorability of labor tasks at the industry level. We match the classification of occupations by offshorability provided by Blinder (2009), available for about 290 SOC codes, to 4-digit NAICS industries. To do this, we need to use SOC crosswalks and information on occupations by industry available from the OES data. In Table A4, we show that industries with inherently a higher degree of offshorability are associated with lower shares and levels of process innovations.

Finally, we rely on patent data to validate our measure. We search for keywords indicating labor-saving technologies in patent descriptions over the period 1995-2012. Such keywords include, for example: *reduce labor, save labor, decrease labor intensity, reduce wage costs, substitute manual workers, replace labor force, reduce manpower.* We next aggregate the number of patents including references to reducing labor costs at the firm-year level for Compustat firms and construct the variable *Share of Patents with Labor References*$_{it}$. In Table A5, we show a positive and significant correlation at the firm-year level between the share of patents with specific references to labor cost reductions and the share or level of process innovations. The correlation instead with product innovations is zero. Note, unlike our process-product innovation measure, patent descriptions do not follow specific set of rules and are, therefore, less reliable. Nevertheless, these correlations are informative and consistent with what we would expect.

[31] The BLS and the National Crosswalk Service Center in the U.S. provide crosswalks that allow us to match the SOC codes in the OES data with the Autor, Levy, and Murnane (2003) job title classifications.

# References


[1] Acemoglu, D., and D. Autor, 2011, "Skills, Tasks, and Technologies: Implications for Employment and Earnings", In D. Card and O. Ashenfelter (Eds.), *Handbook of Labor Economics*, Volume 4, Chapter 12, 1043-1171. Elsevier.

[2] Autor, D. H., F. Levy, and R. J. Murnane, 2003, "The Skill Content of Recent Technological Change: An Empirican Exploration", *Quarterly Journal of Economics*, 118, 1297-1333.

[3] Blinder, A. S., 2009, "How Many U.S. Jobs Might Be Offshorable", *World Economics*, 10, 41-78.

[4] Blinder, A. S., and A. B. Krueger, 2013, "Alternative Measures of Offshorability: A Survey Approach", *Journal of Labor Economics*, 31, 97-128.

[5] Cohen, W. M., and S. Klepper, 1996, "Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D", *Review of Economics and Statistics*, 78, 232-243.

[6] Eswaran, M., and N. Gallini, 1996, "Patent Policy and the Direction of Technological Change", *The RAND Journal of Economics*, 27, 722-746.

[7] Link, A. N., 1982, "A Disaggregated Analysis of Industrial R&D: Product versus Process Innovation", in Devendra Sahal (ed.), The Transfer and Utilization of Technical Knowledge (Lexington, MA: Lexington Books).

[8] Scherer, F. M., 1982, "Inter-industry Technology Flows in the United States", *Research Policy*, 11, 227-245.

[9] Scherer, F. M., 1984, "Using Linked Patent and R&D Data to Measure Interindustry Technology Flows", in Zvi Griliches (ed.), *R&D, Patents, and Productivity* (Chicago: University of Chicago Press for the National Bureau of Economic Research).

## Method of manufacturing a vehicle

US 8317964 B2

### ABSTRACT

A method of manufacturing a vehicle. A set of vehicle body structure components is assembled with interlocking mating features.

| | |
|---|---|
| **Publication number** | US8317964 B2 |
| **Publication type** | Grant |
| **Application number** | US 11/622,164 |
| **Publication date** | 27 Nov 2012 |
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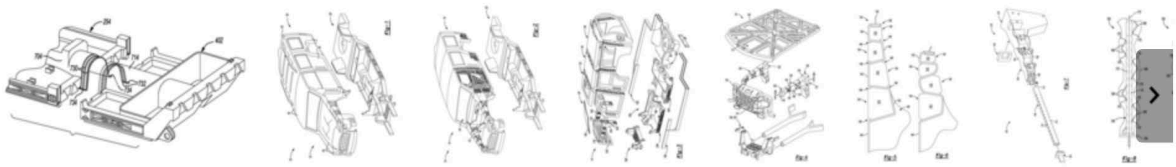
| **Priority date** | 11 Jan 2007 |
| **Also published as** | US20080201952 |
| **Inventors** | Gregory Thomas Hedderly |
| **Original Assignee** | Ford Motor Company |
| **Export Citation** | BiBTeX, EndNote, RefMan |

Patent Citations (99), Non-Patent Citations (28), Referenced by (4), Classifications (25), Legal Events (1)

**External Links:** USPTO, USPTO Assignment, Espacenet

### IMAGES (35)



### DESCRIPTION

BACKGROUND OF THE INVENTION Field of the Invention

The present invention relates to a method of manufacturing a vehicle.

SUMMARY OF THE INVENTION

In at least one embodiment of the present invention, a method of manufacturing a vehicle is provided. The method includes providing a set of cast vehicle body

### CLAIMS (11)

1. A method of manufacturing a vehicle, comprising:

selecting first and second subsets from a set of body structure components;

assembling a floor portion by interlocking members of the first subset, wherein a first member has substantially parallel tunnel ribs that are spaced apart and extend continuously from a first upwardly extending cuff over a tunnel to a second upwardly extending cuff and that are received in

**Figure A1. Method of manufacturing a vehicle**

This figure shows an example of a (purely) process patent comprised of 11 claims. We download the publication from the 'United States Patent and Trademark Office Bulk Downloads' page hosted by Google Inc. at http://www.google.com/googlebooks/uspto.html.

## Integrated sensing display

US 7535468 B2

| | |
|---|---|
| **Publication number** | US7535468 B2 |
| **Publication type** | Grant |
| **Application number** | US 10/873,575 |
| **Publication date** | 19 May 2009 |
| **Filing date** | 21 Jun 2004 |
| **Priority date** | 21 Jun 2004 |
| **Fee status** | Paid |
| **Also published as** | US20060007222 |
| **Inventors** | Michael Uy |
| **Original Assignee** | Apple Inc. |
| **Export Citation** | BiBTeX, EndNote, RefMan |

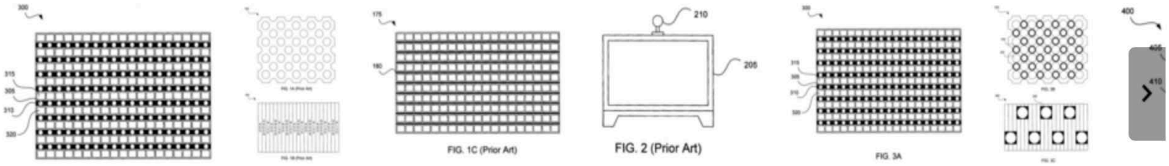
Patent Citations (6), Referenced by (36), Classifications (14), Legal Events (3)

**External Links:** USPTO, USPTO Assignment, Espacenet

### ABSTRACT

An integrated sensing display is disclosed. The sensing display includes display elements integrated with image sensing elements. As a result, the integrated sensing device can not only output images (e.g., as a display) but also input images (e.g., as a camera).

### IMAGES (8)




### DESCRIPTION

BACKGROUND OF THE INVENTION

1. Field of the Invention

The present invention relates to video input and output devices.

2. Description of the Related Art

### CLAIMS (22)

1. A device comprising:

a display panel;

an array of display elements located within the display panel, each display element capable of displaying a pixel of information, either alone or in combination with other display elements; and

**Figure A2. Integrated sensing display**

This figure shows an example of a (purely) product patent comprised of 22 claims. We download the publication from the 'United States Patent and Trademark Office Bulk Downloads' page hosted by Google Inc. at http://www.google.com/googlebooks/uspto.html.

## Table A1: Process and product innovations

This table reports summary statistics on patent claims for the universe of utility patents (Panel A) and the utility patents matched to Compustat firms (Panel B) which applied for at USPTO with application dates from January 1976 till December 2012. Panel A refers to 4,233,476 patents. Panel B refers to 1,855,328 patents. Patent claims define – in technical terms – the scope of protection conferred by a patent, and thus define what subject matter the patent protects. A process claim refers to innovations that reduce production costs, while product claims refer to new goods. An independent claim stands on its own, while a dependent claim, in contrast, only has meaning when combined with a claim it refers to.

| | **Panel A: Universe of Patents** | | | | |
|---|---|---|---|---|---|
| | Mean | Standard Deviation | 25th percentile | 50th percentile | 75th percentile |
| Number of Claims | 15.20 | 12.40 | 7 | 13 | 20 |
| Number of Process Claims | 4.56 | 8.16 | 0 | 0 | 7 |
| Number of Product Claims | 10.70 | 10.50 | 3 | 9 | 15 |
| Number of Independent Claims | 2.70 | 2.29 | 1 | 2 | 3 |
| Number of Dependent Claims | 12.50 | 11.40 | 5 | 10 | 17 |
| | **Panel B: Compustat Firms' Patents** | | | | |
| | Mean | Standard Deviation | 25th percentile | 50th percentile | 75th percentile |
| Number of Claims | 16.00 | 12.60 | 8 | 14 | 20 |
| Number of Process Claims | 5.33 | 8.33 | 0 | 1 | 8 |
| Number of Product Claims | 10.70 | 10.60 | 3 | 9 | 15 |
| Number of Independent Claims | 2.93 | 2.43 | 1 | 2 | 4 |
| Number of Dependent Claims | 13.10 | 11.50 | 6 | 11 | 17 |

## Table A2: Process-product innovation mix: Survey comparisons

This table reports the percentage of R&D performing firms which reported to have introduced process innovations at the National Science Foundation (NSF) survey for the U.S., and the EFIGE (European Firms in a Global Economy: internal policies for external competitiveness) survey for Europe. This number is compared to the universe of Compustat firms with process patents during the same time period. The reported number for the NSF is the average percentage of R&D performing firms doing process innovations over the period 2006-2011 (in particular, it is based on the answers to three NSF surveys: 2006-08, 2008-10, 2010-11). The reported number for Compustat is the average number of firms which have patented process innovations over the 2006-2011 period. The EGIGE survey took place in early 2010 and covers 8 European countries.

| | Source | % of of R&D firms performing process innovation |
|---|---|---|
| U.S. | NSF | 42 |
| U.S. | Compustat | 46 |
| Austria | EFIGE | 48 |
| France | EFIGE | 44 |
| Germany | EFIGE | 43 |
| Hungary | EFIGE | 40 |
| Italy | EFIGE | 45 |
| Spain | EFIGE | 51 |
| UK | EFIGE | 43 |

Table A3: Process-product innovation mix and industry routine job intensity

This table shows the results of OLS regressions of the share of process innovations (Column 1) and level of process innovations (Column 2) in a 4-digit NAICS industry $j$ at time $t$ on a rolling window of 5-year changes of the industry's $j$ routine intensity between $t$ and $t+5$. Innovation measures for each year and industry are computed from the universe of Compustat firms with patent data. To measure the routine intensity of a given occupation, we follow Autor, Levy, and Murnane (2003) and compute the ratio of routine tasks over the sum of all tasks. Routine tasks include the sum of routine cognitive and routine manual tasks and the denominator includes the sum of all routine and non-routine tasks, as defined by ALM. All variables are available in ALM and we match them to occupations at a given 4-digit NAICS industry and year using the OES data and Crosswalks provided by BLS and the Crosswalk Service Center. For a given industry-year, we take the average of routine intensity of the industry's occupations, weighted by employment of occupations at this industry and year. The sample period is 2002-2012. Standard errors are clustered at the 4-digit NAICS industry level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | $\Delta$(Industry Routine Tasks Share)$_{t,t+5}$ | |
|---|---|---|
| | (1) | (2) |
| *Share of Process Innovations*$_{jt}$ | -0.907 | |
| | (0.533)* | |
| *Process Innovations*$_{jt}$ | | -0.132 |
| | | (0.0805)* |
| *Product Innovations*$_{jt}$ | | 0.153 |
| | | (0.119) |
| Year FE | Yes | Yes |
| $R^2$ | 0.06 | 0.06 |
| Obs. | 685 | 685 |

## Table A4: Offshorability and process-product innovation mix

This table reports the results from OLS regressions of the offshorability of occupations at a given 4-digit NAICS industry on the industry share of process innovations (Column 1), and the industry level of process innovations (Column 2). The offshorability of occupations is based on the index provided by Blinder (2009) classifying the offshorability of 291 SOC occupations in the 2004 U.S. workforce. Using crosswalks provided by BLS and the Crosswalk Service Center, we match the index to occupations provided by OES for each 4-digit NAICS-year level. Since the offshorability index is time-invariant, we collapse the innovation measures at the industry level (over the period 2002-2012). Standard errors are robust. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | Process Innovations |
|---|---|---|
| | (1) | (2) |
| *Offshorability* | -0.0161 | -0.0450 |
| | (0.00605)*** | (0.0263)* |
| $Patents_j$ | | 1.370 |
| | | (0.0340)*** |
| $R^2$ | 0.05 | 0.88 |
| Obs. | 176 | 176 |

Table A5: Patents with references to labor and process-product innovation mix

This table reports the results from OLS regressions of the share of patents with references to labor costs on measures of process-product innovation mix. The sample includes Compustat firms for the period 1995-2012. Columns 1-2 include all firm-years, while Columns 3-4 include firm-years for which total number of claims is greater than the sample median. Our dependent variable is based on the count of patents which include keywords indicating reduction of labor costs. Such keywords include: *reduce labor, save labor, decrease labor intensity, reduce wage costs, substitute manual workers, replace labor force, reduce manpower*. All regressions include firm and year fixed effects. Standard errors are robust and clustered at the firm level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Patents with Labor References | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (2) |
| | | | firm patent claims>sample median | |
| *Share of Process Innovations*$_{jt}$ | 0.00245 | | 0.00536 | |
| | (0.0021) | | (0.00306)* | |
| *Process Innovations*$_{jt}$ | | 0.0009 | | 0.0129 |
| | | (0.0004)** | | (0.0005)** |
| *Product Innovations*$_{jt}$ | | -0.0001 | | -0.0007 |
| | | (0.0004) | | (0.0006) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.41 | 0.41 | 0.45 | 0.45 |
| Obs. | 46,078 | 46,078 | 26,068 | 26,068 |

# Appendix B: The 1999 U.S.-China Agreement

Figure B1 presents the timeline of the events surrounding the 1999 U.S.-China bilateral agreement (see Devereaux and Lawrence, 2004). Given the timeline, it is important to emphasize that the information that China was willing to make significant concessions in the negotiations was revealed with the visit of Premier Zhu in the U.S. in April 1999, and was confirmed with the agreement signed a few months later. However, note that some uncertainty still remained as the benefits of the agreement would be fully capitalized if China entered WTO, which required U.S. to grant China permanent normal trade relations (PNTR). The U.S. had to commit to nondiscriminatory treatment by making China's most favored nation (MFN) status permanent, namely give up annual reviews of China's trade status.[32]

Controversy on whether PNTR would be approved by Congress triggered unprecedented lobbying by business interests, which manifests the important investment benefits of the agreement for U.S. firms. Despite the fact that the agreement included provisions that labor unions had supported, such as the antidumping methodology that would remain in force for 15 years after China's accession to WTO and safeguards for certain U.S. domestic industries such as textiles and apparel, labor unions remained strong opponents of the bill.[33] In addition to unions, human rights organizations, consumer groups, and a set of more backward industries (e.g. textile) which feared Chinese imports, were adamantly opposing the bill. The bill seemed to be unpopular among the American public, while a sizable number of the House was publicly against the bill.

On the contrary, big U.S. firms were pushing for the legislation to pass in an organized effort of intense lobbying and advertising campaign.[34] Although the public debate focused

[32]Since 1979, U.S. and China had most favored nation (MFN) trading status, which was subject to an annual review by the U.S.

[33]Two days after the November bilateral agreement, AFL-CIO and 12 industrial unions sent a letter to the Congress asking them to vote against PNTR (Devereaux and Lawrence, 2004).

[34]The United States Chamber of Commerce and the Business Roundtable alone spent $10 million against $2 million spent by labor (Devereaux and Lawrence, 2004).

on exports, U.S. firms were primarily interested in the investment benefits of the agreement. According to a Morgan Stanley Economist, *"debate focused on exports, but for many companies going local is the goal."* The director of global economic policy at the New America Foundation notes: *"U.S. exports will increase over time. But not at the rate of investment, and the corporate community has been quiet about that."*[35] Due to the heated debate, the U.S. business interests were cautious not to provide labor unions with arguments that jobs would be lost because of U.S. companies moving their production to China.

The U.S. House of Representatives voted to grant China PNTR on May 24, 2000 – by a margin of 237 to 197. The Senate approved the bill in September 2000, and the law was signed by the President in October 2000.

[35]The Wall Street Journal, May 25, 2000, A1. See Devereaux and Lawrence (2004).

**Figure B1**

**The 1999 US-China Bilateral Agreement and Permanent Normal Trade Relations (PNTR)**

**1947:** China is one of the 23 original GATT contracting parties.

**1949**: The Chinese Communist Party defeats the Nationalist Party.

**1950**: Nationalist China pulls out of the GATT.

**1951**: President Truman suspends China's most favored nation (MFN) trading status.

**1971**: The United Nations recognizes the Communist government of the People's Republic of China as the sole legal Chinese representative in the United Nations.

**1978**: Deng Xiaoping launches economic reform in China.

**1980:** The United States conditionally restores MFN trading status to China to be reviewed annually under the Jackson-Vanik amendment of the Trade Act of 1974.

**1982:** The GATT grants China's request for nonvoting observer status.

**1986:** China requests the restoration of its status as a full contracting party to the GATT.

**1989:** Unarmed protesters are killed at Tiananmen Square.

**1993:** President Clinton issues an executive order to make China's MFN trade status conditional on improvement in six areas, including human rights.

**1994:** Clinton renews China's MFN status.

**1994:** Beijing accelerates drive to join the GATT, hoping to become a founding member of the WTO.

**1995:** The WTO replaces the GATT.

**1997:** President Jiang Zemin and President Clinton hold a summit in Washington, DC.

**1999:** Chinese premier Zhu Rongji tells US Federal Board Chairman Alan Greenspan that he is ready to make a deal.

**Mar. 1999:** USTR Charlene Barshefsky visits China.

**Apr. 1999:** Premier Zhu Rongji comes to United States. In a controversial move, President Clinton chooses not to close the US-China bilateral.

**May 7, 1999:** The United States mistakenly bombs the Chinese Embassy in Belgrade.

**Sept. 11, 1999:** President Clinton and President Jiang Zemin discuss restarting trade talks during New Zealand Economic Summit.

**Nov. 8, 1999:** Clinton sends USTR Charlene Barshefsky and his economic adviser Gene Sperling to China.

**Nov. 15, 1999:** The US-China bilateral agreement is reached.

**May 24, 2000:** The US House of Representatives votes to grant China permanent normal trade relations (PNTR) status upon its accession to the WTO.

**Sept. 19, 2000:** The US Senate passes PNTR.

**Oct. 10, 2000:** President Bill Clinton signs PNTR.

**Dec. 11, 2001:** China becomes the 143rd member of the WTO.

Source: Devereaux and Lawrence (2004, Exhibit 1).

# Appendix C: Robustness

***Different sample cutoffs for defining high-patenting firms***

In our baseline analysis, we condition our sample on firms having filed for at least 150 patents over the 1995-2004 period. This is important as our main variable *Share of process innovations*$_{it}$ is defined if there is at least one patent for each firm-year and it provides a meaningful measure of the changes in firms' process-product innovation mix only for firms with a non-trivial number of patents. In Table C1, we repeat specifications in Columns 1-3 of Table 3 using different cutoffs to define high patenting firms. In Panel A, we present regressions including all firms in our initial sample. The coefficient on the interaction term is negative and economically significant, but not statistically significant (p-value is 0.18 in Column 1). In Panel B, we restrict the sample to firms with at least 7 patents per year on average (70 patents correspond to approximately the 10$^{\text{th}}$ percentile of the patent distribution). The coefficients are negative and both economically and statistically significant. The results are robust to defining the sample based on cutoffs of 80, 90, 100, or 115 patents over the 10 years of our sample, which correspond approximately to the 15$^{\text{th}}$, 20$^{\text{th}}$, 25$^{\text{th}}$, 30$^{\text{th}}$ percentiles of the patent distribution. Observe that the higher the number of patents per year, and thus the less noisy our measure becomes, the stronger our results. Nevertheless, the coefficients are negative and of similar economic magnitude across all these different samples.

Restricting the sample to intensely patenting firms is less important when considering quantities of process and product innovations. In Table C2, we therefore repeat specifications in Columns 4-9 of Table 3 without restricting our sample on high-patenting firms, which increases our sample size by 1,473 observations. This sample is the same as in Panel A of Table C1. Our results are robust to this alternative sample.

***Allowing for China entry***

In Table C3, we re-estimate our baseline regressions using a time-varying measure of treatment. To this end, we construct an indicator variable $China_{i,t}$ that takes a value of 1

if a firm has a subsidiary in China in a given year $t$ according to its 10-K filings, and use it in the interaction with $Agreement_{(t>1999)}$. The coefficient estimate on the interaction term in the specification with $Process\ innovations_{it}$ is negative and significant at the 1% level. Its magnitude indicates a 4 percentage points reduction in the share of process innovations, which is a 12% reduction relative to the median ratio in the sample. We also show that the quantity of process innovations decreases, while the quantity of product innovations does not change, which confirms our results from Table 3.

***Normalize levels of process and product innovations by R&D and employment***

In Table C4, we repeat specifications in Columns 5-6 of Table 3 for process innovations and in Columns 8-9 of Table 3 for product innovations, where we normalize the levels of process and product innovations by R&D expenditures (Columns 1-4) and by number of employees (Columns 5-8). Our results are robust.

***Negative Binomial model***

Since quantities of process and product innovations are counts, we also consider a Negative Binomial model. In Table C5, we repeat specifications in Columns 4-9 of Table 3 implementing a Negative Binomial model instead of the OLS. The estimated coefficient on the agreement is similar in magnitudes to the OLS results with a negative and significant coefficient at the 1% level for process innovations. Results on product innovations remain small in magnitudes and they are not statistically significant.

***Firm-specific innovation trends***

In Table C6, we control for differential trends based on pre-treatment firm innovation characteristics. In Columns, 1, 3, and 5, we interact year fixed effects with the dependent variable in each case measured in 1998. In Columns 2, 4, and 6, we interact year fixed effects with the number of patents in 1998. We find no evidence that controlling for observable pre-treatment innovation characteristics is driving our results. Our results are robust and they are similar in magnitudes to our baseline results.

***Alternative definitions of process innovations***

Our measures of process innovation are constructed at the claim level. In Table C7, we show that our results are robust to using alternative definitions for our dependent variables. First, we use only independent patent claims to construct our measures, namely we exclude from the analysis claims that are subordinate to other claims. These (dependent) claims may be less important for the innovation. The coefficients in Columns 1-2 are negative and statistically significant at 5% and 10% level respectively for the share of process innovation and negative and significant at the 5% level for the level of process innovation.

Second, we use information at the patent level (instead of the claim level) to construct our measures. In Panel B, Table C7, we define process patents to be all patents with the first claim being a process claim (i.e. (purely) process patents and process-apparatus patents) and we construct the ratio dividing these with the total number of patents. This measure addresses concerns that there might be products (e.g. tools, apparatuses) that can be also used to lower firms' production costs, in which case our claim-based ratio would be under-representing the true mix and level of labor-saving innovations.

In Panel C, we define process patents to be all patents with at least one process claim (i.e. (purely) process patents, process-apparatus patents and product-method patents) which we then divide by the total number of patents. Taking into account all combinations of process and product claims filed into patents, we consider an upper bound for labor-saving technological innovations. Note this measure is very noisy.

The results are robust across specifications. It is worth emphasizing, however, that a patent-based measure is noisy as it also includes, by definition, product innovations. Most importantly, a patent-based measure may be biased due to time-varying differences in patenting practices followed by different firms. This is possible as changes in ways the same number of patent-claims can be combined into patents can erroneously produce different numbers of product and process patents.

***Alternative samples***

Our main identifying assumption is that treated and control firms are similar, except for the fact that treated firms have a presence in China prior to the 1999 U.S.-China bilateral agreement. Table 2 shows that there are no statistical differences across several observables. However, it is still possible that subtle differences between the two groups could lead to different ex-post outcomes. Thus, in this section we perform a matching analysis to minimize pre-treatment differences between the treated and control groups.

We match by size (as measured by sales) and industry (4-digit NAICS) in 1998, one year before the agreement is reached. Matching is done with replacement from the control sample and we keep the closest match. Table C8, Panel A presents the results on share of process innovation (Columns 1-2), process (Columns 3-4) and product (Columns 5-6) innovations. Across specifications we control for firm and year fixed effects and firm level controls. Columns 2, 4, and 6 also control for interacted industry and year fixed effects. Results are robust to this alternative sample and economic magnitudes are very similar to our baseline tests.

In Panel B, we restrict the sample to including control firms with Asian subsidiaries pre-treatment. To even more reduce differences between treated and control firms, we search for control firms with subsidiaries in Hong-Kong and Japan (the more developed, high-wage Asian countries) pre-treatment and exclude those from the analysis. The coefficients for the ratio and level of process innovation are significant at 1% level across specifications. These results, using alternative samples, alleviate concerns that pre-treatment differences in control and treated firms are driving our results.

Table C1: Robustness: Different sample cutoffs for defining high-patenting firms

This table reports results of OLS regressions of the share of process innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms, using different cutoffs to define high-patenting firms. Panel A inlcudes all firms in the initial sample. Panel B includes all firms with 70 patents or more during our sample period ($10^{th}$ percentile). Panel C includes all firms with 80 patents or more during our sample period ($15^{th}$ percentile). Panel D includes all firms with 90 patents or more during our sample period ($20^{th}$ percentile). Panel E includes all firms with 100 patents or more during our sample period ($25^{th}$ percentile). Panel F includes all firms with 115 patents or more during our sample period ($30^{th}$ percentile). $China_i$ is a dummy which takes the value of 1 if a U.S. firm has a subsidiary in China in 1998, and is 0 otherwise. The sample period is 1995-2004. Firm-level controls include Market to Book and firm sales. Controls are defined as in Table 3. All regressions include firm and year fixed effects. Column 3 also includes interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Panel A: All firms | | |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0148 | -0.0162 | -0.0129 |
| | (0.0111) | (0.0117) | (0.0122) |
| Obs. | 3,872 | 3,201 | 3,201 |
| | Panel B: Firms with 70 patents or more | | |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0205 | -0.0226 | -0.0194 |
| | (0.0114)* | (0.0116)** | (0.0120)* |
| Obs. | 3,512 | 2,934 | 2,934 |
| | Panel C: Firms with 80 patents or more | | |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0201 | -0.0217 | -0.0193 |
| | (0.0113)* | (0.0117)* | (0.0122) |
| Obs. | 3,371 | 2,826 | 2,826 |
| | Panel D: Firms with 90 patents or more | | |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0218 | -0.0243 | -0.0208 |
| | (0.0114)* | (0.0115)** | (0.0123)* |
| Obs. | 3,127 | 2,624 | 2,624 |
| | Panel E: Firms with 100 patents or more | | |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0248 | -0.0270 | -0.0252 |
| | (0.0113)** | (0.0115)** | (0.0124)** |
| Obs. | 3,000 | 2,529 | 2,529 |
| | Panel F: Firms with 115 patents or more | | |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0288 | -0.0298 | -0.0259 |
| | (0.0115)** | (0.0116)** | (0.0126)** |
| Obs. | 2,742 | 2,335 | 2,335 |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | |
| Industry×Year FE | | | Yes |

## Table C2: Robustness: Not conditioning on high-patenting firms

This table reports results of OLS regressions of the level of process (Columns 1-3) and product (Columns 4-6) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. The sample and regression specifications are the same as in Columns 4-9 of Table 3, except that we do not require firms to be high patenting. All regressions include firm and year fixed effects. Columns 3 and 6 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Process Innovations | | | Product Innovations | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.128 | -0.124 | -0.128 | -0.0058 | 0.0097 | -0.0188 |
| | (0.0541)** | (0.0566)** | (0.0607)** | (0.0384) | (0.0398) | (0.0422) |
| Firm-level Controls | | Yes | Yes | | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | | Yes | Yes | |
| Industry×Year FE | | | Yes | | | Yes |
| $R^2$ | 0.90 | 0.91 | 0.92 | 0.93 | 0.94 | 0.95 |
| Obs. | 3,872 | 3,201 | 3,201 | 3,872 | 3,201 | 3,201 |

## Table C3: Robustness: Allowing for China entry

This table reports results of OLS regressions of the share of process innovations (Columns 1-3), and level of process (Columns 4-6) and product (Columns 7-9) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. Process and product innovations are log-transformed. $China_{it}$ takes a value of 1 if a U.S. firm has a subsidiary in China in year $t$, and is 0 otherwise. The sample period is 1995-2004. Firm-level controls include Market to Book and firm sales in Columns 2-3, 5-6, and 8-9. Firm-level controls additionally control for patents in Columns 4-9. Controls are defined as in Table 3. All regressions include firm and year fixed effects. Columns 3, 6, and 9 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | | Process Innovations | | | Product Innovations | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $Agreement_{(t>1999)} \cdot China_{it}$ | -0.0411 | -0.0425 | -0.0394 | -0.224 | -0.235 | -0.230 | -0.0027 | -0.0039 | -0.0273 |
| | (0.0122)*** | (0.0126)*** | (0.0130)*** | (0.0567)*** | (0.0584)*** | (0.0597)*** | (0.0397) | (0.0391) | (0.0410) |
| $China_{it}$ | -0.0040 | 0.0012 | 0.0028 | 0.0612 | 0.0368 | 0.0648 | 0.0586 | 0.0170 | 0.0503 |
| | (0.0143) | (0.0134) | (0.0147) | (0.0745) | (0.0670) | (0.0708) | (0.0487) | (0.0498) | (0.0536) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | | Yes | Yes | | Yes | Yes | |
| Industry×Year FE | | | Yes | | | Yes | | | Yes |
| $R^2$ | 0.72 | 0.76 | 0.80 | 0.93 | 0.94 | 0.95 | 0.96 | 0.96 | 0.97 |
| Obs. | 2,399 | 2,051 | 2,051 | 2,399 | 2,051 | 2,051 | 2,399 | 2,051 | 2,051 |

## Table C4: Robustness: Normalize by R&D and employment

This table reports results of OLS regressions of the level of process and product innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. The sample and regression specifications are the same as in Columns 5-6 and 8-9 of Table 3, except that process and product innovations are normalized by R&D expenses in Columns 1-4 and by number of employees in Columns 5-8. Columns 1-4 also control for the logarithm of R&D expenses as a proxy for R&D intensity. All regressions include firm and year fixed effects. Columns 2, 4, 6 and 8 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are robust and clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Log(Process/R&D) | | Log(Product/R&D) | | Log(Process/Emp.) | | Log(Process/Emp.) | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0775 | -0.0832 | 0.0376 | 0.0149 | -0.174 | -0.158 | -0.0178 | -0.0180 |
| | (0.0396)** | (0.0410)** | (0.0388) | (0.0360) | (0.0584)*** | (0.0619)** | (0.0481) | (0.0498) |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes | | Yes | | Yes |
| $R^2$ | 0.94 | 0.95 | 0.96 | 0.97 | 0.94 | 0.95 | 0.95 | 0.96 |
| Obs. | 2,051 | 2,051 | 2,051 | 2,051 | 2,034 | 2,034 | 2,034 | 2,034 |

## Table C5: Robustness: Negative Binomial model

This table reports results of regressions of counts of process (Columns 1-3) and product (Columns 4-6) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. The sample and regression specifications are the same as in Columns 4-9 of Table 3, except that the estimation is implemented by Negative Binomial model. All regressions include firm and year fixed effects. Columns 3 and 6 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Process Innovations | | | Product Innovations | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.143 | -0.173 | -0.176 | -0.0089 | -0.0003 | -0.0185 |
| | (0.0477)*** | (0.0481)*** | (0.0460)*** | (0.0320) | (0.0319) | (0.0320) |
| Firm-level Controls | | Yes | Yes | | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | | Yes | Yes | |
| Industry×Year FE | | | Yes | | | Yes |
| Obs. | 2,399 | 2,051 | 2,051 | 2,399 | 2,051 | 2,051 |

## Table C6: Robustness: Control for firm-specific innovation trends

This table reports results of OLS regressions of the share of process innovations (Columns 1-2), and level of process (Columns 3-4) and product (Columns 5-6) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. The sample and regression specifications are the same as in Columns 2-3, 5-6, 8-9 of Table 3, except that we additionally control for firm-specific trends. In Columns 1, 3, and 5 we interact year fixed effects with the dependent variable defined pre-treatment in 1998 and in Columns 2, 4, and 6 we interact year fixed effects with the number of patents (log-transformed) defined pre-treatment in 1998. All regressions include firm and year fixed effects. Columns 2, 4 and 6 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are robust and clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | Process Innovations | | Product Innovations | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0319 | -0.0321 | -0.161 | -0.177 | -0.0040 | -0.0197 |
| | (0.0124)** | (0.0130)** | (0.0580)*** | (0.0595)*** | (0.0406) | (0.0406) |
| Year FE × $ProcessRatio_{1998}$ | Yes | | | | | |
| Year FE × $Process_{1998}$ | | | Yes | | | |
| Year FE × $Product_{1998}$ | | | | | Yes | |
| Year FE × $Patents_{1998}$ | | Yes | | Yes | | Yes |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes | | Yes |
| $R^2$ | 0.81 | 0.80 | 0.95 | 0.95 | 0.97 | 0.97 |
| Obs. | 2,051 | 2,051 | 2,051 | 2,051 | 2,051 | 2,051 |

## Table C7: Robustness: Alternative definitions of process innovations

This table reports results of OLS regressions of the share of process innovations (Columns 1-2), and level of process innovations (Columns 3-4) on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms.The sample and regression specifications are the same as in Table 3, except that we use alternative definitions for our dependent variables. In Panel A, we construct our measures based on independent claims, i.e. we exclude claims that are subordinate to other claims. In Panels B and C, we use patent-level (instead of claim-level) information to compute our measure. In Panel B, we define process patents as the number of process patents and process-apparatus patents and we divide that with the total number of patents to construct the share of process innovations. In Panel C, we define instead process patents as the number of process patents, process-apparatus patents and product-method patents. In all Panels, Process Innovations in Columns 3-4 are log-transformed. All regressions include firm and year fixed effects. Columns 2, and 4 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level and standard errors are robust and clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | Process Innovations | |
|---|---|---|---|---|
| | Panel A | | | |
| | (1) | (2) | (3) | (4) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0234 | -0.0197 | -0.110 | -0.111 |
| | (0.0104)** | (0.0109)* | (0.0475)** | (0.0508)** |
| $R^2$ | 0.73 | 0.77 | 0.95 | 0.96 |
| Obs. | 2,051 | 2,051 | 2,051 | 2,051 |
| | Panel B | | | |
| | (1) | (2) | (3) | (4) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0360 | -0.0319 | -0.123 | -0.0950 |
| | (0.0142)*** | (0.0149)** | (0.0524)** | (0.0569)* |
| $R^2$ | 0.77 | 0.80 | 0.95 | 0.95 |
| Obs. | 2,051 | 2,051 | 2,051 | 2,051 |
| | Panel C | | | |
| | (1) | (2) | (3) | (4) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0315 | -0.0267 | -0.0645 | -0.0391 |
| | (0.0158)** | (0.0162)* | (0.0397)* | (0.0421) |
| $R^2$ | 0.79 | 0.82 | 0.97 | 0.97 |
| Obs. | 2,051 | 2,051 | 2,051 | 2,051 |
| Firm-level Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes |

## Table C8: Robustness: Alternative samples

This table reports results of OLS regressions of the share of process innovations (Columns 1-2), and level of process (Columns 3-4) and product (Columns 5-6) innovations on treated firms following the 1999 US-China bilateral agreement as compared to a set of control firms. The sample and regression specifications are the same as in Table 3, except that we perform the analysis in different samples. In Panel A, we match by size, proxied by sales, and industry (at the 4-digit NAICS level) based on pre-treatment values in 1998, one year before the agreement is signed. Matching is done with replacement and any firms that cannot be matched are dropped from the estimation. In Panel B, we include in the sample only control firms with Asian subsidiaries pre-treatment, excluding Hong Kong and Japan. All regressions include firm and year fixed effects. Columns 2, 4 and 6 also include interacted 2-digit SIC times year fixed effects. All variables are winsorized at the 1% level. Standard errors are robust and clustered at the firm-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

| | Share of Process Innovations | | Process Innovations | | Product Innovations | |
|---|---|---|---|---|---|---|
| | | | Panel A | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0337 | -0.0395 | -0.161 | -0.180 | 0.0014 | -0.0046 |
| | (0.0196)* | (0.0193)** | (0.0833)* | (0.0838)** | (0.0576) | (0.0614) |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes | | Yes |
| $R^2$ | 0.77 | 0.83 | 0.93 | 0.95 | 0.96 | 0.97 |
| Obs. | 1,357 | 1,357 | 1,357 | 1,357 | 1,357 | 1,357 |
| | | | Panel B | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Agreement_{(t>1999)} \cdot China_i$ | -0.0371 | -0.0362 | -0.191 | -0.204 | 0.0001 | -0.0220 |
| | (0.0135)*** | (0.0137)*** | (0.0670)*** | (0.0716)*** | (0.0418) | (0.0465) |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | | Yes | |
| Industry×Year FE | | Yes | | Yes | | Yes |
| $R^2$ | 0.74 | 0.80 | 0.94 | 0.95 | 0.96 | 0.97 |
| Obs. | 1,627 | 1,627 | 1,627 | 1,627 | 1,627 | 1,627 |