Does offshoring manufacturing harm innovation in the home country? Evidence from Taiwan and China

Lee Branstetter, Carnegie Mellon University, NBER, and Peterson Institute
Jong-Rong Chen, National Central University, Academica Sinica, and National Taiwan University, Taiwan
Britta Glennon, Carnegie Mellon University
Chih-Hai Yang, National Central University, Taiwan
Nikolas Zolas, Census Bureau

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Abstract

Policymakers, managers, management scholars, and economists have long debated the impact of the movement of manufacturing to low-wage developing countries on the innovative capacity of the offshoring firms and countries. On the one hand, offshoring can have a positive effect on home country innovation through efficiency gains and resource reallocation. On the other hand, separating the manufacturing and R&D functions of a firm could degrade the capacity of the firm to engage in some kinds of innovation. Empirical assessment of these conflicting hypotheses has been undermined by a lack of data as well as the endogeneity of changes in offshoring and changes in innovation. We shed light on this debate by studying the impact of Taiwanese high-tech companies' decisions to offshore manufacturing to mainland China on their patenting behavior. In particular, we exploit a policy shock in Taiwan in 2001 that lifted many of the restrictions that had prohibited Taiwanese companies from legally offshoring their manufacturing to China. The response of Taiwan's electronics and IT firms to this policy shock was rapid and substantial – a large fraction of these firms' manufacturing operations shifted to mainland China within just a few years. Using a unique and highly granular panel dataset, combined with a 2SLS estimation strategy that leverages this exogenous policy shock, we identify the causal relationship between offshoring and innovation, and find that offshoring has a negative impact on firm innovation as measured by patents.

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I. *Introduction*

Over the past several decades, there has been a dramatic shift in the global distribution of manufacturing. Driven by the opportunities for cost reduction abroad, many multinationals have offshored much of their production to lower-wage countries while maintaining the skill-intensive activities such as marketing, strategy, and R&D in the home country. Despite this dramatic shift, the consequences of relocating manufacturing operations abroad for firms' ability to innovate are not well understood in the literature. On the one hand, economic theory suggests that there can be important efficiency and specialization gains resulting from this move. In fact, the dominant general equilibrium model of this phenomenon in international economics suggests that such this relocation of manufacturing can raise the global rate of innovation and consumer welfare in both the source and host countries (Helpman 1993; Lai 1998; Branstetter and Saggi 2009). However, other strands of the literature argue that separating the manufacturing and R&D functions of a firm can undermine a firm's innovation capacity by limiting the incentive to innovate in some emerging technologies, reducing the potential for "learning-by-doing", and creating challenges for knowledge transfer and feedback between R&D and production (Pisano and Shih 2009; E. Fuchs and Kirchain 2010; Fuchs 2014a). Despite longstanding interest in this topic, the endogeneity of offshoring and innovation – at the firm, industry, and country level – has made it difficult for researchers to come to definitive conclusions.

In this paper, we seek to shed light on this debate by studying the Taiwanese electronics industry. By the 1990s, Taiwanese firms had become important exporters of electronics and IT hardware, and Taiwanese firms were collectively receiving thousands of patent grants per year from the U.S. Patent and Trademark Office (Branstetter, Li, and Veloso 2015). Practitioner accounts suggest that these firms tended to specialize in the kinds of incremental, process-based innovations that are plausibly most closely connected to manufacturing (Saxenian and Hsu 2001; Ernst 2010; Branstetter 2017). These conditions make Taiwan an especially interesting setting in which to study the potentially negative effects of a firm's relocation of manufacturing to other countries on the innovation activities of the offshoring firm. We exploit a 2001 policy shock in Taiwan to identify the causal relationship between offshoring and innovation, as measured by patenting. This policy shock lifted many of the restrictions that had prohibited Taiwanese companies from legally offshoring their manufacturing to China, and prompted a large and sudden increase in offshoring from Taiwan to China. Other recent studies (Bloom, Draca, and Van Reenen 2016; Autor et al. 2016) have examined the impact of plausibly exogenous import shocks on innovation, but, to the best of our knowledge, no prior paper has identified and exploited a plausibly exogenous shock to the cost of relocating manufacturing across national boundaries within firms to measure the impact on innovation.[1]

To examine the effect of this policy shock, we create a unique and highly granular firm-product data set that captures the offshoring of particular products and components by particular firms. To relate the movement of particular pieces of a firm's manufacturing and product portfolio to China to the firm's innovative activities, as measured by patents, we use keyword generators and text mining algorithms to create a detailed mapping of product categories to patent classes. This

[11] Yang, Wu, and Lin (2010) use firm-level data to examine the response of Taiwanese firms to the deregulation of investment in mainland China we study in our paper, but they do not possess firm-product data, and cannot exploit the product-specific instrumental variables strategy we utilize in our analysis.

allows us to identify the impact of the offshoring of particular products, components, and stages of production on patenting in the areas of technology most likely to be connected to the offshored activity. In doing so, we demonstrate the feasibility of a set of techniques that could be more broadly applied in other papers seeking to identify the effect of trade and FDI shocks on the innovative activities of multiproduct (and multi-industry) firms.

When we apply a 2SLS identification strategy based on the 2001 policy shock to our firm- and product-level data set, we find that offshoring has an enduring, economically and statistically negative impact on the quantity of firm patents in the technological domains that are related to the products it offshored. These empirical results prove impressively robust to a wide range of robustness tests and alternative specifications, and appear to support the view that certain kinds of innovations can be negatively impacted by offshoring. On the other hand, they do not necessarily imply that the technological development of Taiwanese firms was inhibited by the rise in offshoring. In the concluding sections of the paper, we explore the idea that offshoring – and particularly offshoring to low-cost emerging markets – may function as a substitute for certain kinds of (incremental, process-oriented) innovation. We also show some preliminary analysis that suggests that in response to these cost savings, Taiwanese firms reallocated their R&D effort away from cost-reducing innovation and towards product innovation.

II. Does the Relocation of Manufacturing Undermine Innovation? A Literature Review

In the 1980s, the rise of Japan as an increasingly formidable competitor in high-tech industries, the accelerating offshoring of manufacturing by U.S. firms, and the persistence of a significant slow-down in U.S. productivity growth prompted the emergence of an increasingly heated debate between a set of industrialists, policymakers, and management scholars on the one hand and academic economists on the other.[2] Economists generally regarded the offshoring of manufacturing as a rational response to shifting American comparative advantage, and predicted that, as manufacturing declined, other activities would take its place. Economists tended to oppose policies designed to slow or prevent the offshoring of manufacturing, as this would inhibit the efficient and necessary reallocation of U.S. resources across sectors and activities. Industrialists, policymakers, and some management scholars warned that the innovative capabilities of U.S. firms relied on intensive interactions between their R&D centers and their manufacturing operations. These advocates feared that the loss of manufacturing would degrade these innovative capabilities. Popular books like *Manufacturing Matters* (Cohen and Zysman, 1987) openly advocated industrial policies designed to retain some kinds of manufacturing, in order to protect and enhance national innovative capacity.[3]

This debate subsided a bit in the 1990s, as the Japanese economy faltered and the United States experienced a productivity boom disproportionately driven by American-invented software and IT hardware (Oliner and Sichel 2000). However, the acceleration of manufacturing job losses in

[2] Bergsten and Noland (1993)provide a balanced overview of the trade frictions of this era; Prestowitz (1988) is an example of the kind of heated attack on economists' ideas and policy prescriptions that was common at the time.

[3] The view that American innovative capabilities are rooted in manufacturing is still widely held today (Autor et al. 2016); this view is partly based on official statistics that attribute the R&D spending of firms whose operations straddle services and manufacturing into the manufacturing sector. Better accounting in the U.K. and France shows the services sector accounts for a majority of R&D in the former and nearly 50% in the latter ("National Science and Engineering Indicators" 2016).

the 2000s (Autor, Dorn, and Hanson 2013), the slow recovery from the Global Financial Crisis, and a sharp slowdown in productivity growth over the past decade (Fernald 2015) has brought this debate back into policy conversations. By this point, Japanese, Taiwanese, and South Korean observers had joined Americans in worrying that competition from China was undermining their own economic growth and innovative capacity.

Despite the longstanding policy debates surrounding the impact of the relocation of manufacturing on innovation, the empirical literature has not come to a consensus on its sign and empirical magnitude statistically. Economists have tended to take a more positive view of the separation of manufacturing and R&D, arguing that offshoring could have a positive effect on home country innovation. It is important to emphasize, though, that the economists' theoretical arguments are frequently *long-run*, *general equilibrium* arguments, which rely explicitly on a presumed reallocation of resources across firms and industries.[4] Drawing upon the concept of an international product cycle originally proposed by Vernon (1966) and the influential theoretical frameworks introduced by Grossman and Helpman (1991a,b) and Helpman (1993), an extensive literature explores how the shifting of production within multinationals from an industrialized "North" to a lower-cost "South" impacts the rate of innovation within Northern firms (Glass and Saggi 2001; Branstetter and Saggi 2009; Lai 1998). Under a wide range of modeling approaches and parametric assumptions, the shift of production from North to South raises the rate of innovation in the North by freeing up Northern resources, formally used in production, that can now be reallocated to innovation. However, the innovation produced by newly reallocated resources consists of new products introduced by new firms; it does *not* show up within the Northern multinationals shifting production to the South or within the Northern firms who are displaced and imitated.

In contrast, management scholars (and some microeconomists) have tended to focus almost solely on the short-run, partial equilibrium impact of the separation of manufacturing and R&D within the firms engaging in deliberate offshoring of manufacturing. There is considerable controversy in the literature surrounding the sign and magnitude of this effect. In principle, offshoring could help firms increase efficiency and innovation through resource reallocation within the firm (Baldwin and Clark 1997; Quélin and Duhamel 2003). In their influential study of the American disk drive industry, McKendrick, Doner, and Haggard (2000) argue that offshoring enabled U.S.-based disk drive manufacturers to retain a technical lead over their Asian competitors. By shifting manufacturing to lower-cost locations, American firms were able to generate resource savings which was then invested in product-enhancing R&D.[5]

However, other management scholars have argued that separating the manufacturing and R&D functions of a firm could potentially degrade the capacity of the firm to engage in at least some kinds of innovation. The idea that manufacturing and R&D have a closely-knit relationship is not new in the literature. Schumpeter (1939) defined the innovation process as the process of developing an idea from concept into marketable products and processes, a process that requires

[4] An interesting general treatment, with this feature, is provided by Grossman and Rossi-Hansberg (2008).

[5] When manufacturing is offshored to advanced industrial countries rather than low-wage developing countries, a separate strand of the literature argues that this kind of relocation of manufacturing can augment innovation by providing firms with access to local knowledge, resulting in reverse technology transfer and increased depth of knowledge for the firm (Dunning 1998; Florida 1996; Oviatt and McDougall 1994). Economic studies of this phenomenon include Branstetter (2006) and Griffith, Harrison, and Van Reenen (2006).

continuous collaboration, mutual adaptation, and the transfer of learning between those who design and those who manufacture (Kline and Rosenberg 1986; Teece 1996; Pisano and Shih 2009, 2012; Ketokivi and Ali-Yrkkö 2009). In other words, production can provide important feedback and technological learning to R&D, which is crucial for the success of complex products and processes.[6]

Although it seems clear that at least in some industries and product areas, there is the need for continual collaboration and communication between R&D and manufacturing units within a firm, these arguments do not necessarily imply that the two cannot be geographically separated. However, there is a substantial literature detailing the importance of geographic proximity when knowledge transfer – and particularly tacit knowledge transfer – is involved, beginning with theories of agglomeration first articulated by Marshall (1890). Although communication has become easier across geographical distance with the advent of modern telecommunications technologies, an extensive literature documents the obstacles to long-distance knowledge flows that still exist.[7] A separate strand of research has identified another mechanism by which moving manufacturing abroad – especially to a developing country – could reduce some kinds of innovation (Fuchs 2014; Yang, Nugent, and Fuchs 2016; Fuchs and Kirchain 2010a). This strand of research argues that differing production characteristics – and especially wages – can change what innovation is profitable for a firm to do and what products are profitable for a firm to produce. They argue that manufacturing offshore – particularly to low-cost developing economies – can undermine the incentive to innovate in certain kinds of technologies.

A fully comprehensive literature review can be found in Shu and Steinwender (2018), but there are several key ideas that we highlight here, as they guide our own empirical approach and our interpretation of our regression results. The first key idea is that the degree of positive feedback between manufacturing and R&D appears to depend on the nature of the R&D being undertaken.[8] The degree of "positive feedback" between local manufacturing and process-oriented, incremental R&D focused on reducing the costs of existing goods is likely to be significant. The positive feedback between local manufacturing and more fundamental, product-oriented R&D focused on the creation of new goods that are substantively different from those currently being manufactured is likely to be weaker. The second key idea is that process-oriented, incremental, cost-reducing R&D and the offshoring of production to a cheaper location can be viewed as two alternative ways of achieving the same end: lower costs. If the costs of

[6] Japanese industrial and export success in the 1980s was attributed, in part, to the close linkages between design and manufacturing, overlapping product development cycles, and the practice of rotating R&D personnel through marketing and manufacturing operations (Clark et al. 1987).

[7] These include limited ability to observe or describe complex processes at a distance (Argote, Mcevily, and Reagans 2003), the need for physical contact or physical presence when engaging in problem solving (Blinder 2006; Tyre and von Hippel 1997), language and cultural differences (Kogut and Zander 1992), tacitness of knowledge (Brown and Duguid 2007; Audretsch 1998; Leamer and Storper 2001; Patel and Pavitt 1991; Polanyi 1958), the limited codifiability of knowledge (Leamer and Storper 2001), the "stickiness" and "complexity" of knowledge (Patel and Pavitt 1991), high knowledge interdependencies between tasks (Baldwin and Clark 1997), routineness of knowledge (Autor, Levy, and Murnane 2002; Levy and Murnane 2005), and the sheer amount of information (von Hippel 1994). Some papers that have found a negative effect of offshoring on innovation appeal to these constraints of communication and interaction (Fifarek, Veloso, and Davidson 2008).

[8] The level of positive feedback also surely depends on the good being manufactured, but the literature has not yet identified a way of ranking products or industries in order of the degree to which R&D can be separated geographically from manufacturing without loss of effectiveness.

offshoring fall, then rational firms could respond by investing less in incremental, cost-reducing R&D. This decline in R&D does not necessarily represent a technological failure or setback – it occurs because firms can achieve the same ends (lower costs) through different means (less R&D, more offshoring). The third key idea is that a rise in offshoring could, in principle, induce a reallocation of R&D effort within the firm away from incremental, cost-reducing R&D and toward more technologically-ambitious, product-oriented R&D designed to create new and better products rather than cheaper ones. According to McKendrick, Doner, and Haggard (2000), this is what happened inside U.S.-based disk driver firms after they offshored production to Asia. Even if the aggregate amount of R&D investment falls, this reallocation within the firm could raise private profits and social welfare, because the firm still produces (and society still receives) the price reductions in existing goods that large amounts of cost-reducing R&D would have otherwise been required to generate, but it also gets more new products and/or better ones.[9] The fourth key idea is that the degree to which the reallocation within a firm leads to new and better products will be constrained by the extent to which firms possess, or can create within themselves, the capacity to undertake more product-oriented R&D. Firms that have spent their entire history focused on incremental, process-oriented R&D may simply be unable to shift that focus in a radically different direction. In the long-run, there can still be a general equilibrium resource reallocation away from process-oriented R&D-performing firms that cannot change their focus to a different set of firms than can change their focus or have had a more product-oriented focus to their R&D all along. However, an econometric approach that measures relatively short-run effects within firms is likely to miss much of that cross-firm reallocation.

This paper will focus on the impact of relocation of manufacturing on the innovative activities taking place within the offshoring firm, as measured by patents. We thus necessarily retain the short-run, partial equilibrium focus that characterizes much of the management and empirical microeconomic literature we have just summarized. We seek to advance understanding of this impact by going beyond previous empirical studies in three respects. First, we identify a causal relationship between offshoring and innovation that has been complicated by the reality that both are endogenously determined by firms, in response to demand shocks, technological opportunities, and costs that are, at best, imperfectly observed by the econometrician. We exploit a large, exogenous, policy shock, described in detail in the next section, that dramatically reduced the costs incurred by Taiwanese firms in offshoring certain kinds of products and components in the 2000s. This induced a rapid acceleration of offshoring that varied not only across firms, but within firms across products and components. Second, most of our sample firms have a product portfolio that spans multiple product categories. We exploit a unique data source that allows us to observe the offshoring of particular products and components, allowing us to identify which products and components were offshored by which firms (and when) in the aftermath of our policy shock. This allows for a far more granular analysis of the impact of our offshoring shock than would be possible if we were constrained to work with firm-level data (as are many other papers in this literature), rather than the firm-product data we have at our

[9] Klepper (1996) and Cohen and Klepper (1996) draw upon U.S. industrial history to argue that the pace of technological progress slowed in a number of key industries as leading firms shifted from a focus on product-oriented R&D (that was driving rapid experimentation in basic product attributes and functions) to a focus on process-oriented, cost-reducing R&D (designed to win market share for successful products by driving down price). Resource constraints within firms meant that rise in process-oriented R&D necessarily reduced investment in product-oriented R&D. In a sense, offshoring provides a way to reverse this shift.

disposal. Third, we use keyword generators and text mining algorithms techniques to connect the patents generated by our sample firms before and after the policy shock to the products and components in their production portfolio. This allows us to identify the impact of the offshoring of particular products, components, and stages of production on patenting in the areas of technology most likely to be connected to the offshored activity.

This approach is methodologically similar, in some respects, to that undertaken by Bloom, Draca, and Van Reenen (2016) and Autor et al. (2016). These papers exploit the exogeneity of rapidly rising imports from China to measure the impact of intensifying import competition on European and American manufacturers, respectively, while taking into account the fact that many of their firms have product portfolios spanning multiple categories and even industries, and that the intensity of import competition (and innovative effort) varies across sectors. Bloom, Draca, and Van Reenen (2016) find a positive effect of Chinese imports on multiple measures of innovation, while Autor et al. (2016) find a negative effect. Despite the methodological similarities, these papers have different objectives from ours – they seek to measure the impact on innovation of rising import competition rather than the relocation of manufacturing within the firm across national borders. European and American manufacturers, as a group, ran a large and growing trade deficit with China in the 2000s. China's growth had a very different impact on Taiwanese firms' trade flows; Taiwanese manufacturers ran a large trade surplus with China in the 2000s that continued to grow rapidly even as a growing volume of components and products were offshored to Chinese affiliates. For most American and European multinationals, FDI in China remains a surprisingly small component of their global corporate operations. For Taiwanese firms, China has become the overwhelmingly dominant FDI host country.[10] Our focus on policy-induced shocks in the cost of offshoring thus makes sense for our target firms.

III. Taiwan's Policy Change: From "No Haste, Be Patient" (戒急用忍) to "Active Opening, Effective Management" (積極開放有效管理)

Taiwan before the policy change: rapid growth, limited FDI in China[11]

In 1949, Chiang Kai-Shek's Chinese Nationalist Party (often known in the West as the Kuo Min Tang, or KMT) lost the Chinese Civil War to Mao Zedong's Chinese Communist Party and fled to Taiwan with about two million KMT loyalists. There, they set up the Republic of China (ROC) government and claimed that this ROC government was the sole legitimate government of the whole of China. The Chinese Communist Party (CCP) declared that Taiwan was nothing more than a rebellious province, and that the center of the true China remained in Beijing. This set up political tensions between Taiwan and China that remain to this day and that sharply constrained economic interaction across the Taiwan Strait for decades.

[10] It is certainly possible, and even likely, that China's WTO accession made China a significantly more attractive FDI destination for Taiwanese firms. Taiwan's outbound FDI policy change and China's WTO accession were nearly coincident in time, challenging our ability to separate out the impact of these shocks. However, the instrumental variables strategy adopted in this paper exploits the uneven incidence of Taiwanese outbound FDI restrictions across product categories in a manner that should sharpen our ability to identify the impact of the Taiwanese policy shock.

[11] For more detail about Taiwan pre-Chen Shui-Bian, see (Chase, Pollpeter, and Mulvenon 2004; Users 2010)

The KMT's rule over Taiwan was initially politically repressive and authoritarian, but the economic policies it adopted ushered in a long boom that lasted nearly a half century, transforming the island's economy and dramatically raising living standards (Wade 1990). After Chiang Kai-Shek died in 1975, power passed to his son, Chiang Ching-Kuo. The younger Chiang began a gradual transition to a more democratic political system that accelerated as his own health began to fail. Upon Chiang's death in 1988, Lee Teng-Hui assumed the presidency and leadership of the KMT, and continued the transition of Taiwan from dictatorship to multi-party democracy. Unlike his predecessors, Lee was Taiwanese, born to a family that had lived on the island for generations. Whereas the Chiang dynasty had sought an eventual reunification of China and Taiwan (albeit under their own rule), Lee was increasingly suspected of desiring formal independence of Taiwan from China. This led to a dramatic escalation of tensions between the island and the mainland during his presidency.

The gradual liberalization of Taiwan's political system coincided with accelerating structural change in the island's economy. Reflecting the rapid accumulation of physical and human capital during the long boom, the nation's comparative advantage shifted from labor-intensive to skill- and capital-intensive manufactures, and the electronics industry began to emerge as the leading export sector (Wade 1990). After decades of assiduous imitation of foreign technology, Taiwan's increasingly sophisticated manufacturers emerged as innovators in their own right. Taiwanese firms' international patenting took off in the late 1980s and grew rapidly through the 1990s, with a strong focus on the patent classes associated with electronics and information technology. The timing of this patenting explosion coincided with a sharp appreciation of the Japanese yen in the mid-1980s. While Japan's currency rose sharply in value against the dollar and other major Western currencies, the New Taiwan Dollar remained pegged to the dollar; this provided Taiwanese manufacturers with an unanticipated opportunity to undercut their Japanese rivals in price in large, lucrative export markets where the Japanese firms had long had a much stronger market position. Realization of this opportunity required Taiwanese firms to upgrade their quality and reliability significantly. They responded by rapidly increasing R&D and patenting.[12] These investments paid off handsomely; by the mid-1990s, Taiwanese firms had emerged as some of the world's leading manufacturers of semiconductors and computer components.

This success was driven, in part, by the return to Taiwan of a growing number of expatriate Taiwanese engineers and managers who had acquired advanced degrees and valuable work experience in the high-tech industries of the United States (Saxenian and Hsu 2001). Taiwan's rising living standards and increasingly democratic political regime made a return to Taiwan attractive for thousands of such experienced engineers and executives. The growing ranks of these expatriates also helped advance the business models adopted by Taiwanese exporters. With a few exceptions, Taiwanese firms found success through contract manufacturing for other, usually foreign brands. This strategy prioritized a process-oriented, incremental approach to innovation that was focused on cost reduction and the achievement of manufacturing reliability, rather than the kind of radical innovation celebrated in Silicon Valley. As described in the previous section, the literature suggests that firms wedded to this kind of R&D strategy might encounter challenges when their manufacturing began to separate geographically from their R&D.

[12] See Branstetter (2017). Branstetter and Kwon (2016) document a similar rise in R&D and patenting in South Korea, at roughly the same time, in response to similar opportunities.

This period of political and economic change in Taiwan also coincided with a significant shift in economic relations between Taiwan and mainland China. In a sharp break from the policies of his predecessor, mainland leader Deng Xiaoping opened so-called "special economic zones" (three of them in regions proximate to Taiwan), and welcomed Taiwanese investment on the mainland. The same capital and skill accumulation that was shifting Taiwan's comparative advantage away from labor-intensive manufactures to electronics and IT hardware in the early-to-mid 1980s was also pushing Taiwanese manufacturers of textiles and toys to move their production to cheaper locations. China was an especially attractive site; Taiwanese entrepreneurs could, in some cases, establish export-oriented manufacturing facilities in or near their ancestral villages, in partnership with relatives who had remained on the mainland after 1949 (Branstetter and Lardy 2008). Even as Taiwanese production of toys, textiles, and footwear began to shift to the mainland, however, the production of high-tech products tended to remain more concentrated on Taiwan, reflecting the large gaps in manufacturing capability between the two economies.

After he assumed the presidency of Taiwan in 1988, Lee Teng-Hui viewed the growing economic engagement across the Taiwan Strait with concern. By the 1990s, manufacturing facilities based on the Chinese mainland were becoming increasingly adept at producing more complex products, and the much higher factor prices on Taiwan began to entice some Taiwanese electronics manufacturers to consider shifting their more complex products to Chinese factories. Lee, however, feared that this could provide the mainland government with powerful economic leverage over Taiwan's key industries. While he continued to skillfully liberalize Taiwan's political regime, Lee placed limits on economic ties with China that targeted high-technology, defense projects, banking, trade, and investment. In 1996, these regulations were codified in the so-called "no haste, be patient" (戒急用忍) policy. These regulations established a US$50 million limit on any single investment project in China, where any firm that wished to invest over this limit had to be specially approved. In addition, according to this policy, any Taiwanese firm had to limit investments in the mainland to 20-30 percent of its total foreign investment and 20 percent of its investment in Taiwan. A firm's total investment in China could not exceed 40 percent of its net worth. The policy also restricted investments in certain key sectors, including the high-tech sector (for instance, the semiconductor industry was completely banned). Taiwanese firms were prohibited from investing in major infrastructure projects on the mainland and from setting up high-tech research and development facilities.[13]

IIIb. Policy change under Chen Shui-Bian: "Active Opening, Effective Management"[14]

In the mid-1990s, Lee Teng-Hui ushered in constitutional changes that allowed for the direct election of the president. He won the first of these elections himself in a historic vote widely

[13] In reality, this policy was not totally effective in stopping the flow of capital to China; some investment slipped in through intermediaries like the Cayman Islands and Hong Kong. However, there were some high-profile instances of high profile companies and individuals being fined for illegal investment in mainland China before the policy change (for example: UMC, SMIC, Robert Tsao, Richard Chang, Tsai Juei-chen, Tsai Kuan-ming), indicating that the regime was not entirely toothless. In short, the policy restrictions constrained - but did not entirely halt - FDI in China.

[14] For more detail about Taiwan under Chen Shui Bian's controversial presidency, see Wang (2002); Tung (2005); Tanner (2007); J. J.-F. Yang 2010; and Chen (2003).

regarded by international observers as free and fair.[15] The constitutional changes also placed term limits on Taiwanese presidents – limits Lee honored by allowing another KMT candidate to run for the office in 2000. In the 2000 election, however, democracy activist and longtime dissident Chen Shui-Bian won the presidency, an unexpected outcome for most observers. Chen's Democratic Progressive Party (DPP) had never won a presidential election in Taiwan before; in fact, he "won" the 2000 election with only 39% of the vote. Facing a legislature still controlled by the KMT and a business community skeptical of his candidacy, Chen Shui-Bian sought to build support for his new administration by taking a much more conciliatory approach to economic relations with the mainland than his predecessor. This approach, under the premise of "integration theory," was reiterated in a series of speeches over his first term.[16] In addition to the desire to build an internal coalition that would support his nascent administration, Chen also wanted to secure Taiwan's admission into the World Trade Organization (WTO), which would require the adoption of more open policies on trade and investment. Mainland China was on the verge of admission, and Taiwan did not want to be left out of the organization its giant neighbor was about to join.

In January 2001, the Three Mini Links (小三通) policy was enacted, legalizing direct trade, postal service, and travel between Quemoy (Kinmen) and Matzu in Taiwan, and the adjacent ports of Fuzhou and Xiamen in China, for the first time since the Chinese Civil War. Then, President Chen established the Economic Development Advisory Committee (EDAC or 經發會) to discuss ways to stimulate Taiwan's economy and plan future economic development. Cross-Straits economic relations were one of five key areas of discussion. On August 26, 2001, the EDAC made a series of recommendations designed to replace the "no haste, be patient" policy, all of which subsequently became government policy.[17] In November 2001 the government formally announced the replacement of the "no haste, be patient" policy with the "active opening and effective management" (積極開放有效管理) policy. As part of the policy, the investment ceiling of US$50 million on individual investments was removed, and all projects with a value of less than US$20 million were automatically approved. The most important change of the new policy for our purposes was the removal of 122 high-tech projects from the list of "prohibited categories," including laptops, mobile phones, digital optical drives, computer hardware and software, communication products, and consumer electronics.[18]

The new regime continued to subject the mainland investment of Taiwanese firms to a number of regulations and restrictions. Any single investment project over US$20 million still had to go through a special review system. The US$50 million ceiling on individual investments was replaced by an annual ceiling on total corporate investment in the mainland. The ban on

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[15] The mainland government responded to this vote with ominous warnings, missile tests, and military exercises. The U.S. government was so concerned by the threats emanating from the mainland regime of Jiang Zemin that President Bill Clinton ordered a U.S. Navy carrier task force to enter the Taiwan Strait – long regarded by China as territorial waters – as an unmistakable expression of support for Taiwan.

[16] See his [English version] inaugural speech http://www.mac.gov.tw/ct.asp?xItem=50894&ctNode=5913&mp=3&xq_xCat=2000 and Cross-Century Remarks [English version] http://www.mac.gov.tw/ct.asp?xItem=50875&ctNode=5913&mp=3&xq_xCat=2001

[17] See "EDAC outlines cross strait ties" http://taiwaninfo.nat.gov.tw/ct.asp?xItem=18913&CtNode=103&htx_TRCategory=&mp=4

[18] The complete list of products, identified by their HS code, is in the appendix.

investment by Taiwan's semiconductor industry[19] was initially retained, but gradually relaxed over the next several years. Remaining restrictions notwithstanding, the costs of offshoring production to the mainland fell substantially as a result of this policy change, stimulating a rapid increase in the amount of offshoring to China.[20] We exploit the differential cost effect of the policy on different products; products that were moved from the "prohibited" to "allowed" categories became much less costly to offshore.

On the other side of the Taiwan Strait, China's formal entry into the WTO in late 2001 constituted a temporally coincident policy shock that plausibly increased Taiwanese firms' interest in investing in the mainland. We acknowledge this coincidence, but do not believe it seriously undermines our empirical strategy. While mainland China's WTO-mandated opening to foreign trade and investment varied across major industry groups, our sample firms are all in one industry (electronics). As such, the China "WTO" shock probably impacted all our firms in a similar way. We maintain that the Taiwanese policy shift still induced a reduction in offshoring costs that varied across firms and products, and this difference can be used to shed light on the impact of offshoring on innovation.

IIIc. Aggregate impact of the reform

As we have already acknowledged, the pre-2001 restrictions did not completely eliminate FDI in China by Taiwanese firms, even in "prohibited" categories. Some investment took place via offshore financial centers such as Hong Kong or the Cayman islands. Nevertheless, Taiwanese firms were taking a significant risk in violating explicit government investment bans, and this limited the scope, scale, and nature of FDI on the mainland. Once Chen Shui-Bian's administration formally relaxed these restrictions, investment by Taiwanese firms surged. Between 2000 and 2004, officially recorded annual flows of outbound FDI from Taiwan to the mainland nearly tripled. By 2011, annual flows were five times greater than in 2000 (Ministry of Economic Affairs, 2016).

A large fraction of this FDI was vertical in nature; Taiwanese firms sought to use their Chinese subsidiaries as export platforms from which to serve the global market (Branstetter and Lardy 2008). While Taiwan's imports from China grew rapidly after 2001, Taiwan's exports to the mainland grew even faster, reflecting, in part, the provision of parts and components to their mainland subsidiaries. Official statistics from Taiwan, taken from Tanner (2007) and plotted in Figure 1, provide evidence supporting this characterization of Cross-Straits trade. We can see that that there was an increase in trade between China and Taiwan after 2001, and we can see that Taiwan's trade surplus with the mainland grew rapidly, even as Taiwan's imports from China also grew. Thus, Taiwan's "China shock" was quite different from the trade shocks visited

[19] For more information about the semiconductor industry's move to mainland China, see (Klaus, 2003; C. Yang and Hung, 2003)

[20] The new framework introduced by the Chen Administration continued to influence Cross-Straits trade even after Chen left office in 2008. His successor, KMT candidate Ma Ying-Jeou, also sought to expand Taiwanese trade and investment with the mainland, and eventually concluded the so-called Economic Cooperation Framework Agreement (ECFA) with mainland China, but this had relatively little impact on Taiwan's electronics industry over our sample period.

upon the United States and Western Europe, whose manufacturers ran large and rapidly growing trade deficits with China.

Our firm and product level offshoring data is described in more detail in the next section, but it includes customs data, detailing all exports leaving China between 2000 and 2011 by firm. This means that we can observe whether there was an increase in exporting from Taiwanese subsidiaries in mainland China over this time period. Figure 2, constructed from our dataset, demonstrates that there is a striking increase in the total value of exports from our sample firms' subsidiaries in mainland China.

IV. Data Sources

One of the major contributions of this paper is the matching of multiple databases, at both the product and firm level, such that we can measure the impact of the offshoring of particular products, by particular firms, on innovation in technologies associated with that product. This section describes that data construction process in detail; Figure 3 provides a diagrammatic summary of the matching process.

Identifying Taiwanese firm sample

First, we compiled a list of 823 Taiwanese electronics firms from the Taiwanese Stock Exchange under the category of electronics (電子工業).[21] These were condensed into 792 firms as several pairs of firms turned out to be affiliated and some firms did not exist in 2000[22]. We link Taiwanese parent firms to their R&D expenditures and to their USPTO patents so that we can measure how their patenting and R&D expenditures changed after the policy shock. The R&D expenditure data set contains quarterly data of R&D spending under the category of sales expenditure between 1996 and 2008. We annualized the data, assuming R&D maintenance across quarters when there was missing data for a quarter. Of the 792 parent firms, 711 had data on R&D expenditures. The sales data set contains calendar year data for total revenue between 1999 and 2013.[23]

Patent data

In the paper, we use United States patent grants as an indicator of innovative output for our sample firms. Use of patent data is essential, because we have no way of allocating recorded R&D expenditures to individual products. However, the detailed patent classes assigned to patented inventions allow us to link patenting in particular technological domains to the products offshored by our sample firms. While a long literature exploits patents as measures of technological activity, many papers have indicated that the value distribution of patented inventions is highly skewed (Harhoff et al. 1999). Prior research has shown that more valuable

[21] http://mops.twse.com.tw/mops/web/t51sb01

[22] Combined firms: Wistron NeWeb Corp and Wistron Corp; Hon Hai and Foxconn; BenQ and Qisda; Lite-on companies; Pegatron and Asus; Hannstar companies; Arima companies; Chunghwa companies; Compal companies; Inventec companies; Nan Ya companies; Quanta companies; PCHome companies. Firms that did not exist in 2000: ADATA, Edison-Opto, MStar Semiconductor, Chimei Innolux, and Nuvoton.

[23] Unfortunately, neither R&D data nor sales data are broken down by product.

patents tend to be patented abroad as well as at home (Jaffe and Trajtenberg 2002).[24] Therefore, use of data on Taiwanese firms' U.S. patents will tend to capture more valuable inventions than those granted solely by the Taiwan Intellectual Property Office (TIPO). Prior research confirms that more valuable inventions are more highly cited (Hall, Jaffe, and Trajtenberg 2001), and in robustness checks, we will weight Taiwanese firms' U.S. patents by the number of forward citations they receive. We obtained data on all utility patents granted by the USPTO between 1976 and 2017 and matched 88,526 patents to 490 of the 792 firms by name, using a time-intensive, manual screening procedure that ensured no misspelled or alternatively written firm names were missed. The data are constructed from the August 2017 release of the PatentsView Database[25]. The patent data contain information on patent number, all assignee names, all assignee codes, grant year, application year, forward citations, and IPC codes.

Chinese customs data

In order to link parent companies in Taiwan to their subsidiaries in mainland China, we then collected a list of 2,887 mainland Chinese subsidiaries founded between 1996 and 2008 that match to 664 of the 792 Taiwanese parent firms. These were found by checking each parent company website for information on their subsidiaries in mainland China and by checking the Taiwan Stock Exchange's Market Observation Post System (MOPS),[26] which provides the official annual reports of all publicly listed companies in Taiwan. Those Chinese subsidiaries were then matched to export data in the mainland China customs dataset (中国海关进出口统计数据), which has also been used by Manova and Zhang (2012) and many other researchers. We extracted all exports originating from the Chinese subsidiaries of Taiwanese parent firms between 2000 and 2011. We match exports to 1,011 subsidiaries (and 331 parent firms), again using a careful manual screening to ensure no alternatively written subsidiary names were missed. We constructed a concordance across the different versions of the HS codes across in different years of the customs database (1996, 2002, and 2007). These data contain information on subsidiary name and ID, year of export, HS code, value, quantity, price, unit, and destination country.

These are the data we use to capture the increase in offshoring induced by the Chen Administration's relaxation of outbound FDI restrictions. They come with significant advantages and disadvantages, and it is important that we be clear about both. After linking these customs data to the mainland subsidiaries of our Taiwanese firms, we can observe the inception and expansion of exports of particular products by the mainland subsidiaries of particular Taiwanese firms. We assume that this expansion of exports from mainland subsidiaries comes at the expense of production of the same product by the same firm on Taiwan. Contemporary press accounts and other sources confirm that, in many cases, export expansion by Chinese subsidiaries really did reflect a shift of export-oriented production from Taiwan to China.

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[24] Prior research and press accounts show that, in the aggregate, Taiwanese electronics firms are enthusiastic users of the U.S. patent system and tend to patent their more valuable inventions there with high frequency (Ellis, 2014).

[25] www.patentsview.org Patentsview is supported by the Office of the Chief Economist in the US Patent and Trademark Office, and is a collaboration between USPTO, USDA, the Center for the Science of Science and Innovation Policy, New York University, the University of California at Berkeley, Twin Arch Technologies, and Periscopic.

[26] http://mops.twse.com.tw/mops/web/index

However, we necessarily measure this production shifting with error, because we have no way of directly observing the cessation of production of particular products by the Taiwanese parent.[27] We also have no way of breaking down the domestic sales of these mainland subsidiaries by product. If Taiwanese firms are exporting to Chinese customers from factories in Taiwan, and then replacing these exports with production on the mainland, none of which is exported outside of China, we will miss this offshoring entirely.[28] These challenges imply that we measure offshoring with error, potentially leading to a downward bias in our regression estimates. To the extent that Taiwanese firms offshore production to sites other than China, our measure will fail to capture that.[29] We also fail to capture the offshoring of production by Taiwanese firms to unaffiliated domestic Chinese manufacturers rather than their own affiliates.[30] However, since our instrumental variables strategy relies on measurement of offshoring induced by the Chen Administration's reform of FDI policy, and that reform was specific to FDI in China, these omissions do not necessarily undermine our empirical strategy. Finally, and perhaps most significantly, our Chinese export data are not available before 2000. This means we have very limited data on offshoring prior to the policy shock, and we possess no practical means of controlling for the existence of "pre-trends" in offshoring that might be present in advance of our policy shock.

Linking customs data to patent data

The last stage of our data construction is the linkage of the customs data to the patent data. Patents are organized using the International Patent Classification (IPC) system while the customs data uses an industry classification system called Harmonized System (HS) codes. The difficulty in matching them stems from the fact that the two classification systems are motivated by different objectives. The IPC system is intended to allow patent examiners to identify the novel technical features of the invention while industry systems like the Harmonized System are intended to disaggregate traded products according to their form and function. Since goods in very different categories can use the same underlying technologies, this make construction of a concordance from IPC codes to HS codes extremely difficult. As a result, most past efforts in the literature to link patent classes to industry codes or HS codes have either been highly aggregated or have relied on old concordances whose usefulness has been undermined by rapid technological change in key domains (Verspagen, Moergastel, and Slabbers 1994; Schmoch, Laville, and Patel 2003).

However, a new methodology introduced by Lybbert and Zolas (2014), using keyword generators and text mining algorithms, allows us to generate more disaggregated concordances between IPC patent classes and the HS codes in the customs data. This approach is called the Algorithmic Links with Probabilities (ALP) approach and we follow the same methodology used

[27] We can measure the total value of our Taiwanese firms' sales, but we cannot break those sales down by product.

[28] We have no way of breaking down the domestic sales of our firms' mainland subsidiaries by product. However, in the context of the Taiwanese-Chinese relationship, our focus on Taiwanese firms' exports from their Chinese subsidiaries is defensible. As Rosen and Wang (2011) and Branstetter and Lardy (2006) document, Taiwanese firms investing in China have intensively used China as an export base.

[29] Industry-level data reveal that China was by far the most important host country for Taiwanese electronics firms' FDI over our sample period.

[30] Industry sources assert that most Taiwanese production shifting to China occurred via their own affiliates.

in the original paper here, but with HS codes instead of SITC and ISIC codes. The broad approach is as follows. First, we generate keywords from the HS classification descriptions that are robust to standard misspelling issues, relevant to the economic category, and should retrieve specific patents. This initial set is also expanded to include relevant synonyms using WIPO's PATENTSCOPE, and then manually inspected and refined. Next, we data mine patent abstracts and titles in the PATSTAT database using the keywords we just generated and generate a list of patents that matched the search. We then compile a frequency of IPC classes that matches to each industry. We reweight these results in a way that minimizes Type I errors and factors in both the raw frequencies and the specificity of each technology class (or how frequently an IPC subclass appears in the PATSTAT database). These distributions create linkages from patents to economic data and vice versa, and can then be used for industry-level analyses of the relationships between patent classes and industry codes. After linking patents and exported products, we have 669 unique HS-6 digit product codes indexing patents and/or exports.

Aggregating product groups

With 483 firms and 669 product codes, our data is highly sparse and noisy, so we aggregate these product codes using K-means clustering. To define technologically proximate patenting industries, we cluster our 669 product categories using various *K*-means clustering algorithms based on certain criteria found in each of the products. The criteria used to generate our clusters include yearly patent output for all 669 product categories (in 1000's) from 2000-2011 based on the 2-digit IPC technology weights from Lybbert and Zolas (2014)[31], yearly exports (in $B) from 2000-2011 and a binary indicator for whether or not the policy change affected the product category (1/0). Our *K*-means clustering algorithm considers all of the criteria in determining which clusters to place each of the product codes.

To generate clusters, we first calculate a dissimilarity matrix across each of the available criteria. To calculate the dissimilarity matrix and to ensure our results are robust, we utilize three separate distance calculations for each criterion. We utilize two of the most frequently used methods for generating distances, and an additional method that is specialized for continuous and binary data (which fits our data).

*Euclidean Distance***:** This is typically the default dissimilarity measure, used primarily for continuous data that sums up the squared differences for each criterion between each of the product codes.

$$\left\{\sum_{i=1}^{I}(x_{ki}-x_{ji})^2\right\}^{1/2}$$

Canberra Distance: This is another commonly used measure for continuous data, that takes on a value between 0 and *I* (number of criteria that is being considered). It is sensitive to small changes near zero, which may help in weighting our distance measures. The formula is given by:

[31] We use 2-digit IPCs to cluster rather than the more disaggregate 4-digit IPCs, as the more disaggregate technology weights have too little overlap across industries, resulting in very few, tiny clusters.

$$\sum_{i=1}^{I} \frac{|x_{ki} - x_{ji}|}{|x_{ki}| + |x_{ji}|}$$

Gower Distance[32]: This algorithm can be used for continuous and binary data. It is somewhat similar to the Canberra measure for continuous data, but it utilizes a different weighting scheme for the differences. Because our data consists of both continuous and binary measures, this will be our primary algorithm, with the other algorithms used as robustness checks. The formula is given by:

For binary variables - $$d_{ijv} = \begin{cases} 0 & \text{if } x_{iv} = x_{jv} \\ 1 & \text{otherwise} \end{cases}$$

For continuous variables –

$$d_{ijv} = \frac{|x_{iv} - x_{jv}|}{\left\{\max_k x_{kv} - \min_k x_{kv}\right\}}$$

We next define the number of clusters we would like to categorize our 669 product categories. To determine the optimal number of clusters, we attempt to minimize the within-cluster sum of squares (WSS) based on the number of clusters. In doing so, we perform the "elbow method" which computes the within-cluster sum of squares for a different value of *k* for each of the *k*-means clustering algorithms listed above. We perform this for up to 50 clusters and plot the results for the Gower distance algorithm in Figure 4.

The "elbow method" tells us to identify the inflection point where the within-cluster sum of squares flattens out as additional clusters are added. From Figure 4, we see that this occurs between *k=15 – 20*.

This tells us that adding additional clusters greater than 20 does not necessarily reduce the within-cluster sum of squares and generally creates more noise as products will be arbitrarily separated based on the criteria we have listed above. Finally, we can generate our clusters for the 669 product groups using *K*-means and random *K*-centering (the starting point for calculating the distance from our criteria is randomly chosen) based on the aforementioned algorithms. Ultimately, we settle on 16 clusters using the Gower distance measure as our baseline, but we include robustness checks for the other clustering measures in the Appendix.

Final sample

[32] Reference: Gower, J. C. (1971), "A general coefficient of similarity and some of its properties". *Biometrics*, 27, 623—637.

Over the course of this matching process, we lose a number of firms; only 483 of the original 792 firms do at least some patenting or offshoring. This sample attrition is not random; there are systematic differences between firms that patent and offshore and those that do not. However, the remaining firms are the ones that are economically important for Taiwan; the large number of smaller firms that we exclude are mostly inconsequential. However, this sample attrition implies that we are measuring the average treatment effect only for multinational firms who do at least some patenting or exporting from China.

There are multiple ways that we can define our sample, depending on how we treat observations in years where there are no matched patent applications and/or no exports listed for that firm-product. In our base sample, we include a firm-product cluster in all years if there was either patenting or offshoring in that firm-product cluster at some point during our time period. We thus allow for firm entry into and exit from both offshoring and patenting. We include regressions on other sample definitions in the Appendix.

Table 1 shows the summary statistics for our data.

V. Empirical Methodology and Results

We use several empirical models to estimate the impact of offshoring on patenting. Our base model exploits the correlation within firms and products and over time between offshoring and patenting, combined with the sharp increase in offshoring caused by the policy shock to infer the relationship between offshoring and innovation. We are interested in what happens to patenting in a product cluster for a given firm when that cluster gets offshored. We use the following OLS long-differences model:[33]

$$\ln(I_{ijt}) - \ln(I_{ijt=2000}) = \beta_0 + \beta_1[\ln(Off_{ijt}) - \ln(Off_{ijt=2000})] + \Delta\epsilon_{ijt}$$

where *i* indexes the firm, *j* indexes the product grouping, and *t* indexes time in years. As noted previously, innovation ("*I*") is proxied by patents, and offshoring ("*Off*") is proxied by the stock of measured exports from Chinese subsidiaries. Patents are indexed by application year[34] while exports are indexed by year of export. We use a long-differencing model to remove any fixed effects for firms or product clusters rather than a fixed effects model due to data constraints; we only observe one year before the policy shock occurs. We take each difference at the product-firm level between a post-policy year (2003-2011) and a pre-policy year (2000). All standard errors are clustered at the firm level[35].

We present coefficient estimates from an OLS specification as a baseline. Table 2 reports the results, which reveal a small, positive, statistically significant correlation between offshoring and patenting within a firm and product class that appears to persist across long differences of

[33] There are zeros in our data, so in order to use natural logs we add one to all observations.

[34] To better reflect the date that the innovation actually occurs, we use the application date for granted patents rather than the grant date.

[35] There are too few product groupings to cluster standard errors at the product level; Angrist and Pischke (2009) note that clustering standard errors when there are fewer than 42 clusters introduces the risk of bias. Therefore, in our main specifications, we do not cluster our standard errors at the product level. However, we do later show robustness checks that show our results are robust to product-clustered standard errors.

varying length. However, these results are subject to a number of identification concerns, including the presence of time-varying unobservable demand shocks that raise both offshoring and innovation. Imagine a successful Taiwanese firm that confronts rapidly growing demand for some subset of its products in advanced country markets. In order to expand production of these products, it may establish subsidiaries in China that can produce these products on a larger scale (and at lower cost). At the same time, the firm will seek to increase its research effort in the technologies underlying these successful products, and the results of that effort will show up as increased patenting in the classes linked to these products.

To address this concern, we use a 2SLS strategy that exploits the policy shock described in Section III. As noted in that section, a new party came to power in Taiwan in 2000, and in 2001 they lifted offshoring restrictions on 122 product categories. This presents us with a source of product-level variation; different products were affected differentially by the policy shock. We divide products into two categories: products that were directly impacted by the policy change, and products that were unaffected (so that they either continued to be banned or continued to be approved). Although we have acknowledged evidence of limited illegal offshoring of some of these "banned" products prior to 2001, we interpret the policy change as an exogenous reduction in cost for firms wishing to offshore in those categories. We create an indicator variable to divide the two product groups and use this as our instrument. The baseline category is products unaffected by the policy change.

In the first stage, we regress the logged differenced stock of exports on our created indicator variable:

$$\Delta ln\left(exports_{ijt}\right) = \alpha_0 + \alpha_1 Affected_{ijt} + \varepsilon_{ijt}$$

In the second stage, we use the predicted differenced export stock from stage one in the second stage regression, again using long differences:

$$\Delta\ln(Pat_{ijt}) = \beta_0 + \beta_1 \Delta\ln(\widehat{exports}_{ijt}) + u_{ijt}$$

For this instrument to be valid, our instrument needs to be highly correlated with the potentially endogenous variable. We can measure this directly by looking at the F test of excluded instruments from the first stage results, reported in each 2SLS regression table; these tests clearly show that our instrument is strongly correlated with exporting. We must also assume that the products and firms that were impacted by the policy shock were not systematically more or less technologically dynamic than the ones that were unaffected. This is tantamount to assuming that, whatever technological opportunity shocks might have been affecting our sample firms, there were no systematic differences in the incidence and direction of these shocks between affected and unaffected product categories. Provided this assumption holds, our exogenous policy shift only affects patenting through changes in offshoring and is unrelated to time-varying unobservable factors like product-specific demand and technology shocks. Is this assumption a reasonable one?

A close examination of the details of the policy shift provide grounds for believing that it is. The text describing the investment restrictions that were retained by the Chen Administration emphasizes international conventions prohibiting trade in certain goods, weapons-related

technologies, and investment in mainland infrastructure. These would not appear to be systematically related to important positive or negative technological opportunity shocks impacting Taiwanese electronics firms.[36] The 122 policy categories that were liberalized in 2001 are revealed, upon close inspection, to be a mix of both high-tech and low-tech products, but, if anything, the list of formerly-prohibited-but-now-permitted categories seems biased in the direction of high-tech products with significant underlying technological opportunity for further innovation, including laptops, mobile phones, digital optical drives, and computer hardware and software. The products affected by the FDI regime change would appear to be more likely, rather than less likely, to benefit from positive technological opportunity shocks after the policy shift, possibly biasing us in the direction of finding a *positive* relationship between offshoring and innovation. The fact that our 2SLS regressions consistently indicate a negative relationship is therefore reassuring.

However, we must exercise a degree of caution regarding our treatment of the semiconductor industry. In contrast to computer hardware, laptops, and digital optical drives, semiconductors were not fully liberalized in 2001. Instead, liberalization in this sector proceeded gradually, over the next several years, in a manner that appeared to involve a considerable degree of discretion on the part of the Chen Administration. Press accounts suggest that this approach was motivated by a desire to keep the most technologically dynamic parts of Taiwan's semiconductor industry – presumably the parts facing the most significant technological opportunities – on Taiwan. In earlier versions of the paper, we considered the semiconductor industry to be "unaffected" by the FDI regime change, because only a few firms were allowed to invest in China. That classification decision could raise concerns about the validity of our identifying assumptions, given the eventual size of the semiconductor industry and its relatively strong performance in terms of patent growth over time.

To deal with these concerns, we exclude the semiconductor sector[37] from our baseline specifications. To deal more systematically with the possibility that some of our other firm-product "clusters" are becoming more technologically dynamic than others even before the FDI policy shift, we also reran regressions explicitly controlling for "pre-trends" in the firm-product level patenting data. Our results are qualitatively robust to the inclusion of these controls as well. Finally, we note that our IV approach passed a series of over-identification and endogeneity tests.[38]

Table 3 shows the baseline 2SLS results, which suggest that our concerns about a potential upward-bias in the OLS regressions due demand shocks or other time-varying unobservables may have been well-founded. When we instrument for offshoring using the policy shock, instead of finding a positive effect as in the OLS regressions, we instead find a negative and statistically significant effect on patenting. This holds whether we measure exporting in value or quantity. The results show that a 100% increase in the stock of exporting causes a roughly 2-4% decline in

[36] For decades, Taiwan has heavily relied on weapons provided by the United States for its national defense. In contrast to Israel, Russia, or, increasingly, mainland China, Taiwanese firms are not considered to be innovators in weapons-related technologies. And, for obvious reasons, innovation in weapons-related technologies is systematically less likely to be patented than innovation in other domains.

[37] Defined as HS 8541-8542, and 8486.

[38] This includes all the standard tests that accompany the ivreg2 command in Stata: Kleibergen-Pap, Anderson-Rubin Wald, Stock-Wright, and Hausman.

patenting for a firm-product pair, relative to the amount of patenting growth that would have happened without offshoring.

Robustness Checks

Taiwanese firms tend to specialize in incremental, process-based innovations, which typically generate fewer forward citations. We therefore also run our 2SLS regression on citation-weighted[39] patent counts to identify whether the negative effect on patenting is stronger for patents with higher citations. Table 4 presents results of the 2SLS regression on citation-weighted patent counts and shows very little difference between the citation-weighted results and the patent count results. While this might suggest that offshoring equally affects both incremental, process-based innovation and highly-cited significant innovation, a look at the distribution of forward citation of Taiwanese patents illustrates that the vast majority are not cited at all. This raises issues of interpretation that we will return to later in the paper.

Table 5 shows results from the subsamples of firms who both offshore and patent. The results presented in these tables are consistent with the earlier regressions, showing a negative effect of offshoring on innovation, even for the subset of firms who are active in both offshoring and patenting.

Patents are a relatively rare event; their distribution has a long right tail. We dealt with this in the previous specifications by applying OLS but transforming patents to be ln(patents + 1). Adding one to the observations can – in some situations – create bias, so we also utilized a count data model – IV Poisson - that is well-equipped to deal with these kinds of distributional challenges. In these specifications, we move the base patent value to the right-hand side of the equation, since count data models cannot be run on dependent variables with negative values. Results are shown in Table 6, and demonstrate that our results are not driven by any issues with our transformation; they still show a negative effect of offshoring on innovation. Note that the coefficients are much smaller because patent counts and export value are no longer logged, so the interpretation is different. These results are shown with product-clustered standard errors as a further robustness check.

An appendix, available from the authors upon request, contains further robustness checks, briefly described here. These robustness checks include additional controls, including firm-level R&D spending in 2000, patent pre-trends by product cluster, and firm-level revenue in 2000. These results continue to show a negative and statistically significant effect. We also exclude firm-product "outlier" observations as defined by observations with DFBETA greater than one or greater than 2/sqrt(n). Finally, although our primary product aggregation method, as described in the data section, used a Gower clustering algorithm, we also used the Canberra clustering algorithm and the Euclidean clustering algorithm as robustness checks; results are robust to these alternative clustering methodology, as well as to different numbers of clustering.

The results are robust to these different specifications, suggesting that the significant increase in offshoring by Taiwanese firms to China in response to President Chen's 2001 policy change

[39] We use the total count of forward citations divided by (2012-current year) to address potential citation truncation concerns.

significantly slowed the growth in patenting by Taiwanese firms in the affected product categories relative to the growth in patenting that would have happened had manufacturing of those products remained in Taiwan.

VI. Discussion and Extensions: Did offshoring change the nature and focus of Taiwanese firm R&D and patenting?

Our results collectively provide robust evidence that an increase in offshoring can have a negative impact on firm innovation, at least in some contexts. However, the social welfare implications of this negative effect should be interpreted with care. At least one plausible interpretation of our negative coefficient is that offshoring and the innovation it displaces are alternative means to the same end. If many of the foregone patents were for process-oriented, cost-reducing innovations, then Taiwanese firms may have been able to realize cost reductions through offshoring more cost-effectively than if they had tried to achieve the same degree of cost reductions through process-oriented R&D. If this is the case, then our finding that the volume of innovation declined as offshoring increased may be misleading. Just because offshoring and innovation may be substitutes, as our negative coefficient implies, does not necessarily mean that firm performance or social welfare are undermined when a decline in the cost of the former leads to a reduction in the latter.

If offshoring allowed Taiwanese firms to realize cost reductions in a more cost-effective way than through incremental, process-oriented R&D, then it could have spurred a reallocation of research effort within Taiwanese firms. While we cannot allocate the R&D spending reported by Taiwanese firms to different R&D projects, our patent data indicate that, after our policy shift, patenting grew more slowly in the firm-product clusters in which the policy shift induced more offshoring, but patenting grew more quickly in firm-product clusters that were unaffected by the policy shift. Prior research suggests a different dimension along which reallocation may have taken place: a shift away from incremental, process-oriented R&D and toward R&D that enhanced product capabilities or enabled the creation of new products altogether. This reallocation could have been welfare-enhancing, even if it did not expand the total number of patents.

In this section, we provide some suggestive evidence that this in fact is what happened; that Taiwanese firms changed their research portfolio after offshoring escalated, towards more product innovation and away from process innovation.

We utilize the methodology pioneered by Ganglmair and Robinson (2018), who generously shared their classification data for our paper, to define patents as either process or product patents. Complete details of their methodology can be found in their working paper, but the general idea is that patents are classified based on the language of the claims. Since lawyers write patent claims in a standardized language, and they are written in very different ways for a process or product, the authors can exploit the different grammatical structures and keywords to identify whether it is a process or product claim. Examples of a product vs a process claim are in Table 7. There are then three separate ways to define a patent as a process or product patent, based on the associated claims. These are as follows: (1) if at least 50% of the associated claims

are process claims, (2) if the first claim is a process claim, and (3) if any of the associated claims are process claims.

Figure 5 shows the portfolio of patents for Taiwanese firms and demonstrates results consistent with the hypothesized resource reallocation mechanism. The graph shows that the portfolio of process and product patents by Taiwanese firms did indeed change significantly in the early 2000s, beginning at the same time as the offshoring policy shock. Taiwanese firms seemed to have shifted from a portfolio made up of 50-50 process-product patents to a portfolio dominated by product patents. This is true regardless of which of the three patent classification definitions is used.

We run two additional descriptive regressions to examine whether the aggregate portfolio change across Taiwanese firms can be statistically seen when looking within firms. We use the following Poisson model:

$$ProductPatents_{it} = \delta_1[\ln(Off_{it})] + \delta_2 ProcessPatents_{it} + \alpha_i + \epsilon_{it}$$

where i indexes firms and t indexes years. ProductPatents is the count of product patents by firm i in year t, ProcessPatents is the count of process patents by firm i in year t, and $\ln(Off_{it})$ is the total export value of firm i in year t. We can also do the reverse, with the product patent count on the right hand side and the process patent count on the left hand side. Both regression results are shown in Tables 8 and 9. Table 8 shows a positive relationship between firm-level offshoring and the number of product patents, while Table 9 shows no relationship between firm-level offshoring and the number of process patents. These results are not causal, but they are suggestive of the idea that Taiwanese firms reallocated their research effort in response to offshoring, and in particular that this reallocation may have taken place as a shift away from incremental, process-oriented R&D and toward R&D that was product-oriented. This reallocation could have been welfare-enhancing, even if it did not expand the total number of patents. Current ongoing research efforts are underway to establish a causal link between offshoring and this kind of reallocation.

VII. Conclusions

Over the last several decades, the phenomenon of offshoring has dramatically shifted the global distribution of manufacturing. This shift has prompted debate about the long-term impact of this shift on the innovative capacity of the offshoring firms and countries. Academic economists and some management scholars have generally taken a benign view of this shift, arguing that it allows for a redistribution of resources across firms, products, and industries that is likely to increase innovation, at least in the long run, within the home country of the offshoring firms. Industrialists, policymakers, and some management scholars dispute this, emphasizing that geographically separating manufacturing and R&D could degrade the innovative capacity of offshoring.

Efforts to assess the empirical salience of either view have been hampered in the past by a lack of appropriate data and by the potential endogeneity of both offshoring and innovation. Our paper makes progress on both fronts. Exploiting a plausibly exogenous policy shock in Taiwan that followed the unexpected outcome of the 2000 presidential election, we adopt a 2SLS

identification strategy that gives us empirical leverage around identifying the causal impact of offshoring on innovation. Because of the unique circumstances facing Taiwanese electronics firms, we are also able to capture their offshoring in a uniquely granular way following this policy shock. We are able to use machine learning techniques to map the offshoring of particular products and components to patenting by the same firms in the same product areas, allowing us to explore the implications of offshoring for innovation within as well as across firms.

We find robust evidence from 2SLS regressions that an exogenous rise in offshoring *reduced* innovation in patent classes associated with the products that were offshored. These findings are consistent with the view that the effectiveness of certain kinds of R&D is linked to proximity to local manufacturing, and that investment in that kind of R&D declines when manufacturing moves away. On the other hand, preliminary analysis of the changing portfolio of Taiwanese firms points to the possibility of a reallocation of R&D effort within firms across products and from cost-reducing R&D to more fundamental product innovation. More detailed and precise exploration of that reallocation, and the extent to which it is plausibly attributable to exogenous declines in the price of offshoring, is the focus of ongoing research.

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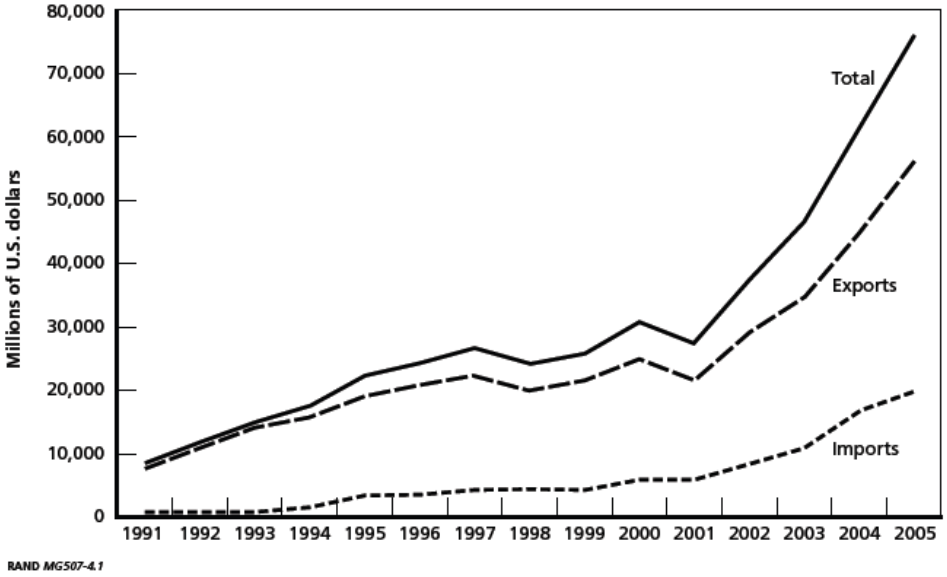
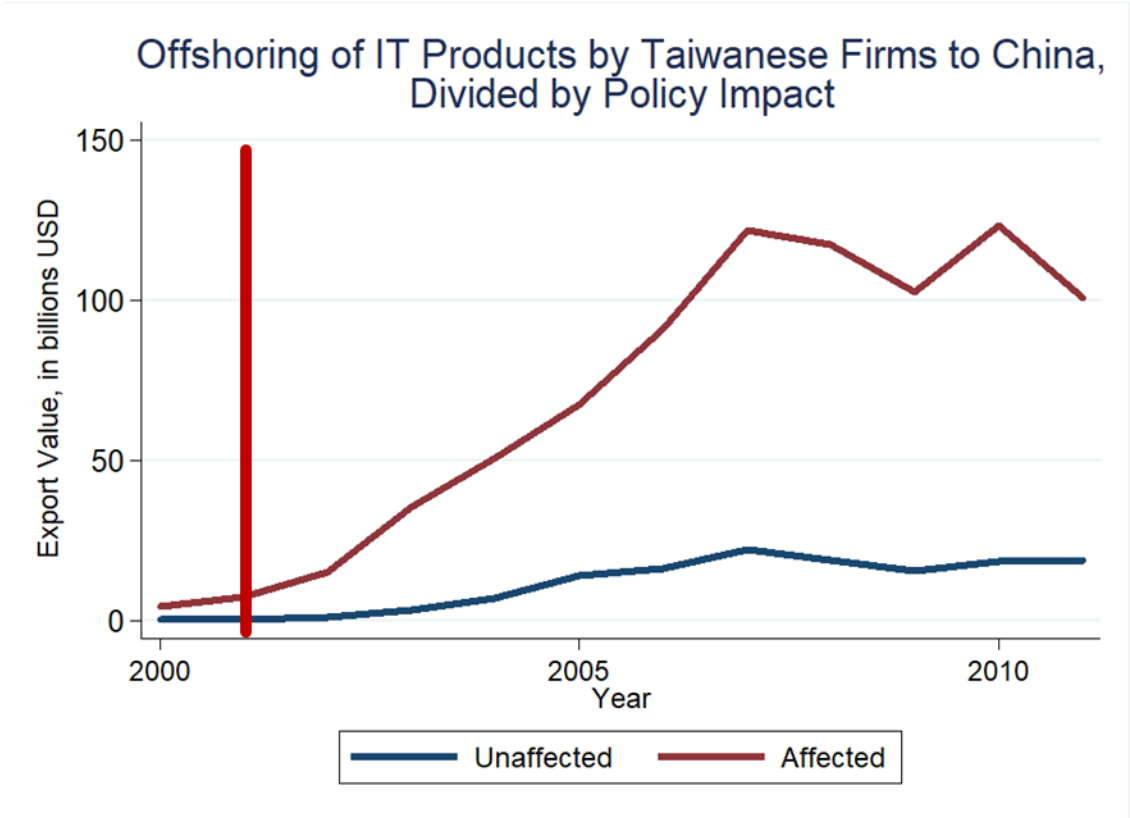
Figure 1: Cross-Strait Trade 1990-2005



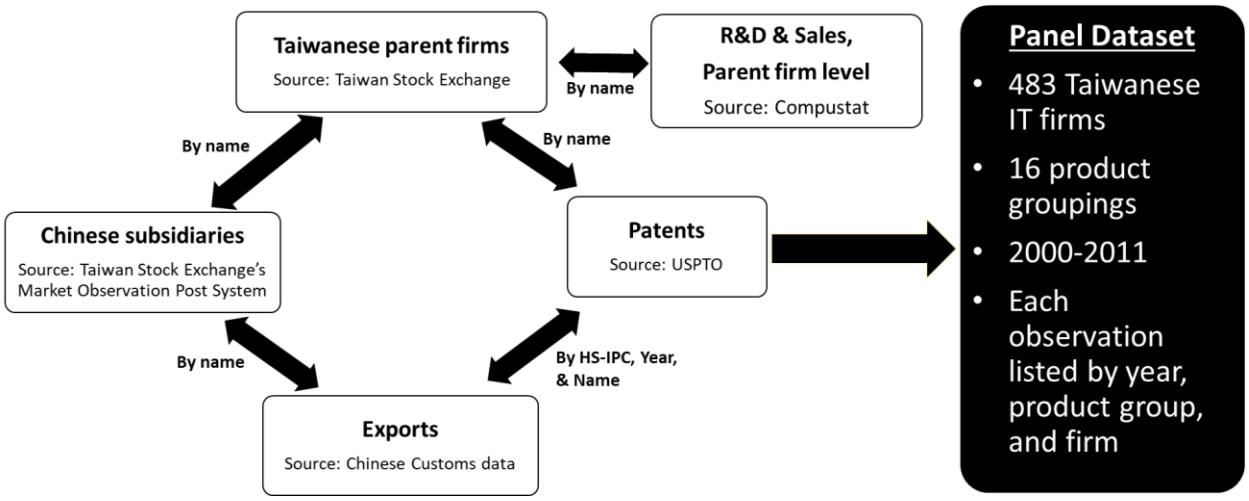
Notes: Each line shows, from top to bottom, total trade, exports, and imports between China and Taiwan in millions of U.S. dollars over time, as reported using official statistics from Taiwan. The figure is pulled from Tanner (2007).

Figure 2: Exports from Taiwanese Subsidiaries in China



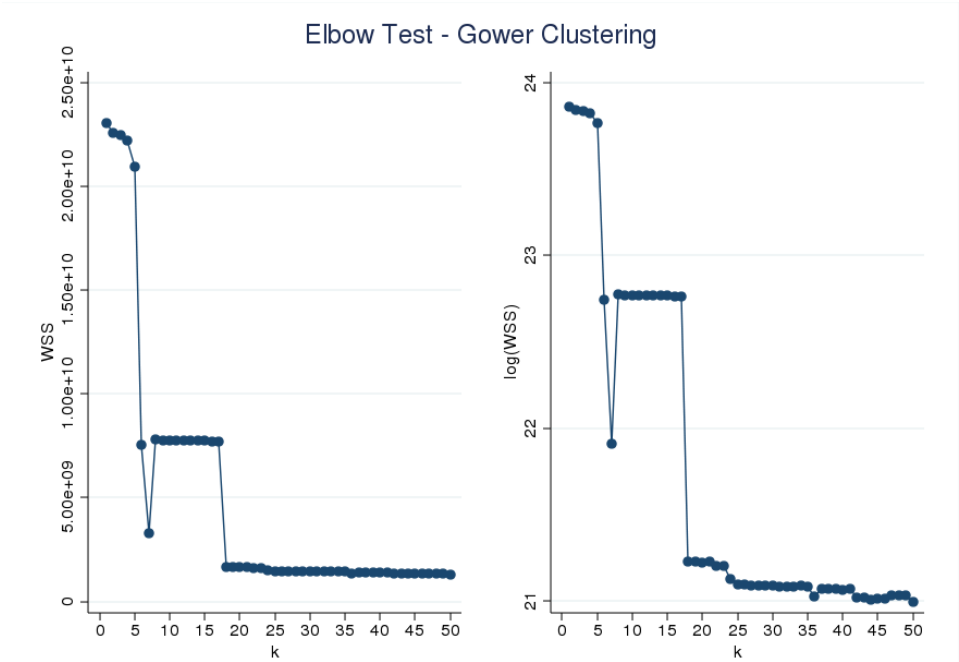
Notes: These lines show the total value of exports from the Taiwanese subsidiaries in China of the Taiwanese multinationals in our sample over time, in billions of USD. We have divided the exports into two categories: those affected by the 2001 policy change, and those unaffected by it. The red line indicates the time of the policy change.

Figure 3: Data Summary



Notes: The above figure shows all the datasets and sources combined for the paper, and how they were combined.

Figure 4: Elbow test to determine optimal number of clusters



Notes: The "elbow method" tells us to identify the inflection point where the within-cluster sum of squares flattens out as additional clusters are added. From this figure, we see that this occurs between *k=15 – 20*.

Figure 5: The changing patent portfolio of Taiwanese firms

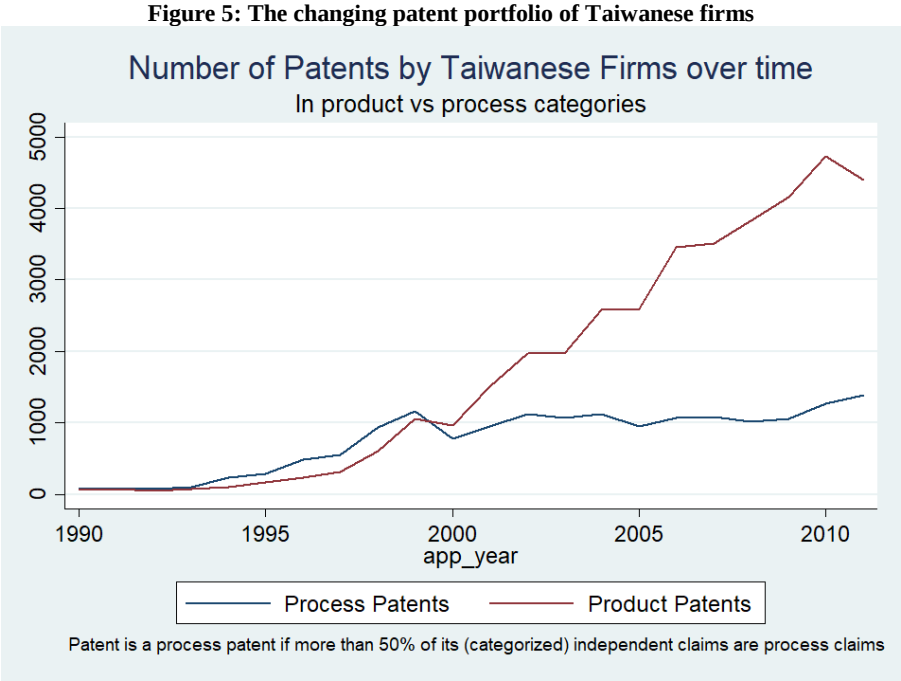


Table 1: Summary Statistics

	Mean	Std Dev	Min	Max	N
Patents per firm	94.13	727.49	0	15,316.73	483
Export value per firm (USD)	2,103,652,993	14,078,901,514	0	185,887,235,200	483
Patents per product category	2,525.88	4,694.59	0.06	17,455.31	18
Export value per product category (USD)	56,448,021,985	124,601,418,509	18,027,450	518,647,609,692	18
Patents per year	3788.82	1806.55	1216.12	6075.83	12
Export value per year (USD)	84,672,032,978	56,155,459,295	5,716,500,884	149,783,582,544	12

Notes: This table provides some summary statistics for the two key variables in our regressions: USPTO patents by Taiwanese firms in specific product clusters, probability weighted according to their IPC-HS match, and export value by Taiwanese firms in specific product clusters in USD.

Table 2: OLS Regression, Effect of Logged Differenced Export Value on Logged Differenced Patent Counts

VARIABLES	(1) 2003-0	(2) 2004-0	(3) 2005-0	(4) 2006-0	(5) 2007-0	(6) 2008-0	(7) 2009-0	(8) 2010-0	(9) 2011-0
LD_lval_stock	0.00660***	0.00754***	0.00776***	0.00772***	0.00811***	0.00518**	0.00466*	0.00449*	0.00309
	(0.00208)	(0.00229)	(0.00228)	(0.00244)	(0.00231)	(0.00233)	(0.00253)	(0.00230)	(0.00225)
Constant	0.0228**	0.0564***	0.0788***	0.110***	0.112***	0.143***	0.149***	0.139***	0.147***
	(0.0106)	(0.0131)	(0.0154)	(0.0171)	(0.0187)	(0.0203)	(0.0217)	(0.0209)	(0.0211)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665
R-squared	0.007	0.009	0.009	0.008	0.010	0.004	0.003	0.003	0.001

Standard errors in parentheses
Standard errors clustered at the firm level
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the long difference of the natural log of the probability-weighted patent count for a firm-product cluster between 2000 and a given year. Each column represents a different long difference, ranging from 2003 to 2011. The probability weights on the patent counts are generated by the Algorithmic Links with Probabilities approach that generates a concordance between IPC patent classes and HS codes. LD_lval is the long difference of the natural log of the value, in US dollars, of export stock from China by Taiwanese firms, between 2000 and the same given year. The specifications are OLS specifications, and firm-level cluster-robust standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3: 2SLS Regressions, Effect of Logged Differenced Export Value Stock on Logged Differenced Patent Counts

VARIABLES	(1) 2003-0	(2) 2004-0	(3) 2005-0	(4) 2006-0	(5) 2007-0	(6) 2008-0	(7) 2009-0	(8) 2010-0	(9) 2011-0
LD_lval	0.000899	-0.00674	-0.0255**	-0.0324***	-0.0242***	-0.0259***	-0.00348	-0.0138	-0.0230**
	(0.0107)	(0.00905)	(0.0103)	(0.0116)	(0.00928)	(0.00977)	(0.00892)	(0.00938)	(0.0104)
Constant	0.0347	0.0959***	0.195***	0.273***	0.266***	0.305***	0.194***	0.246***	0.308***
	(0.0290)	(0.0327)	(0.0428)	(0.0532)	(0.0494)	(0.0563)	(0.0535)	(0.0615)	(0.0688)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665
First stage F	22.78	32.38	29.73	32.44	44.30	45.93	45.84	44.15	37.02

Standard errors in parentheses
Standard errors clustered at the firm level
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the long difference of the natural log of the probability-weighted patent count for a firm-product cluster between 2000 and a given year. Each column represents a different long difference, ranging from 2003 to 2011. The probability weights on the patent counts are generated by the Algorithmic Links with Probabilities approach that generates a concordance between IPC patent classes and HS codes. LD_lval is the long difference of the natural log of the value, in US dollars, of export stock from China by the same Taiwanese firms in the same product cluster, between 2000 and the same given year. The specifications are 2SLS specifications, where the instrument is a dummy variable set to one if the product cluster was affected by the 2001 policy change, and zero otherwise. Firm-level cluster-robust standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4: 2SLS Regressions, Effect of Logged Differenced Export Value on Logged Differenced Forward Citation-Weighted Patent Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**2003-0**	**2004-0**	**2005-0**	**2006-0**	**2007-0**	**2008-0**	**2009-0**	**2010-0**	**2011-0**
LD_lval_stock	-0.00468	-0.0131	-0.0285***	-0.0383***	-0.0268***	-0.0318***	-0.0152	-0.0303***	-0.0531***
	(0.0101)	(0.00838)	(0.0108)	(0.0115)	(0.00876)	(0.00972)	(0.00935)	(0.0114)	(0.0160)
Constant	0.0269	0.0879***	0.173***	0.254***	0.240***	0.308***	0.248***	0.364***	0.586***
	(0.0266)	(0.0294)	(0.0435)	(0.0521)	(0.0468)	(0.0568)	(0.0583)	(0.0740)	(0.107)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665
First stage F	22.78	32.38	29.73	32.44	44.30	45.93	45.84	44.15	37.02

Standard errors in parentheses
Standard errors clustered at the firm level
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the long difference of the natural log of the probability and citation-weighted patent count for a firm-product cluster between 2000 and a given year. Each column represents a different long difference, ranging from 2003 to 2011. The probability weights on the patent counts are generated by the Algorithmic Links with Probabilities approach that generates a concordance between IPC patent classes and HS codes. To adjust for truncation, the citation weight is the average number of forward cites per year that each patent has received. LD_lval is the long difference of the natural log of the value, in US dollars, of export stock from China by the same Taiwanese firms in the same product cluster, between 2000 and the same given year. The specifications are 2SLS specifications, where the instrument is a dummy variable set to one if the product cluster was affected by the 2001 policy change, and zero otherwise. Firm-level cluster-robust standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5: 2SLS Regressions, Effect of Logged Differenced Export Value on Logged Differenced Patent Counts, for firms that offshore and patent

VARIABLES	(1) 2003-0	(2) 2004-0	(3) 2005-0	(4) 2006-0	(5) 2007-0	(6) 2008-0	(7) 2009-0	(8) 2010-0	(9) 2011-0
LD_lval_stock	-0.00684	-0.00963	-0.0245**	-0.0341***	-0.0296***	-0.0296***	-0.0111	-0.0186**	-0.0236**
	(0.0100)	(0.00838)	(0.00954)	(0.0114)	(0.00942)	(0.00966)	(0.00840)	(0.00917)	(0.0103)
Constant	0.0658*	0.128***	0.236***	0.340***	0.351***	0.381***	0.260***	0.316***	0.361***
	(0.0381)	(0.0430)	(0.0556)	(0.0718)	(0.0678)	(0.0758)	(0.0703)	(0.0826)	(0.0934)
Observations	2,458	2,458	2,458	2,458	2,458	2,458	2,458	2,458	2,458
First stage F	25.21	35.48	32.82	33.80	45.55	45.94	45.60	43.46	36.65

Standard errors in parentheses
Standard errors clustered at the firm level
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the long difference of the natural log of the probability-weighted patent count for a firm-product cluster between 2000 and a given year. Each column represents a different long difference, ranging from 2003 to 2011. The probability weights on the patent counts are generated by the Algorithmic Links with Probabilities approach that generates a concordance between IPC patent classes and HS codes. LD_lval is the long difference of the natural log of the value, in US dollars, of export stock from China by the same Taiwanese firms in the same product cluster, between 2000 and the same given year. The specifications are 2SLS specifications, where the instrument is a dummy variable set to one if the product cluster was affected by the 2001 policy change, and zero otherwise. The regression is performed on a subsample of Taiwanese firms who do both offshoring and patenting. Firm-level cluster-robust standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6: IVPoisson Regressions, Effect of Differenced Export Value Stock on Differenced Patent Counts

VARIABLES	(1) PatCount_2003	(2) PatCount_2004	(3) PatCount_2005	(4) PatCount_2006	(5) PatCount_2007	(6) PatCount_2008	(7) PatCount_2009	(8) PatCount_2010	(9) PatCount_2011
LD val_stock	-5.81e-07***	-2.33e-07***	-1.18e-07***	-8.64e-08***	-2.30e-08***	-1.24e-08***	-7.04e-09**	-5.56e-09***	-3.81e-09***
	(1.26e-07)	(6.52e-08)	(2.37e-08)	(1.45e-08)	(3.82e-09)	(2.29e-09)	(3.14e-09)	(1.56e-09)	(1.32e-09)
PatCount_2000	0.295***	0.255***	0.258***	0.328***	0.345***	0.341***	0.284**	0.300***	0.265***
	(0.0598)	(0.0658)	(0.0479)	(0.0520)	(0.0543)	(0.0594)	(0.118)	(0.0786)	(0.0847)
Constant	-0.962***	-0.473	-0.479*	-0.272	-0.267	-0.0721	0.186	0.0659	0.106
	(0.269)	(0.295)	(0.277)	(0.283)	(0.315)	(0.325)	(0.366)	(0.360)	(0.350)
Observations	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665	3,665

Standard errors in parentheses
Standard errors clustered at the product level
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the probability-weighted patent count for a firm-product cluster in a given post-policy year. The probability weights on the patent counts are generated by the Algorithmic Links with Probabilities approach that generates a concordance between IPC patent classes and HS codes. LD_val_stock is the long difference of the value, in US dollars, of export stock from China by the same Taiwanese firms in the same product cluster, between 2000 and the same given year. PatCount_2000 is the count of patents in 2000. The specifications are IVPoisson specifications, where the instrument is a dummy variable set to one if the product cluster was affected by the 2001 policy change, and zero otherwise. Product-level cluster-robust standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 7: Product vs Process Claim Examples

Product Claim Example
A computer programmed with a set of machine language instructions for carrying out a set of functions so as to assist an observer to analyze a cytological specimen via a microscope screening station, wherein said microscope screening station comprises a microscope with a lens and a motorized stage for moving said specimen across said lens, and said set of functions comprises, in combination: 1. *receiving a set of digital data representing an image of said specimen, said image being comprised of pixels;* 2. *analyzing said digital data and thereby identifying cytological material in said specimen;* 3. *maintaining in a data storage medium a set of spatial coordinates indicative of each of a plurality of regions of said specimen that collectively contain the cytological material that said computer identifies in said specimen; and* 4. *generating a routing path keyed to said coordinates, wherein (i) said routing path defines a sequence for presentation of said regions to a human observer via said microscope, (ii) said sequence is arranged to minimize movement of said specimen across said lens, (iii) said routing path defines for each of said regions a speed for movement of said specimen across said lens, and (iv) said speed for each given region is a function of at least a distribution of cytological material that said computer identifies respectively in said given region,* 5. *whereby, said routing path may be applied to control movement of said motorized stage so as to present said regions to said human observer via said microscope according to said sequence and speeds, and whereby said speed will be slower for regions containing more cytological material than other regions, thereby allowing said human observer more time for analysis of said regions containing more cytological material, and vice versa.*
Process Claim Example
A method for the manufacture of security paper, such as banknote paper, which method comprises forming a papermaking suspension comprising cellulosic fibers and polyvinyl alcohol fibers wherein the cellulosic fibers are present in an amount of at least 80% of weight of the total weight of the fibers in the suspension, characterized in that the polyvinyl alcohol fibers are soluble in water at temperatures of from 95 degrees to 100 degrees C, are 3 to 5 mm in length, and are present in an amount of from 2% to 10% by weight based on the weight of the fibers, wherein the papermaking suspension comprising cellulosic fibers and the polyvinyl alcohol fibers is dewatered through an embossed wire mesh, where the embossing creates a profile of peaks and troughs corresponding to the light and dark areas of the watermark, and the thus formed paper with the watermark feature after dewatering is thereafter dried to provide the resulting security paper.

Notes: Examples of a product and a process claim from (Ganglmair and Robinson 2018). Analysis is both keyword-based and also utilize grammatical structure analysis. Process claims will use words like “method” or “process” and will often have a standardized structure such as “A method of X comprising the steps of […]”. Product claims also have some keywords like “device” or “machine” but are typically less easy to classify. Process claims will typically have a series of steps, while product claims will instead use many nouns and adjectives.

Table 8: Poisson with Firm Fixed Effects, Regressing the Number of Product Patents on Firm-level Offshoring, Controlling for the Number of Process Patents

VARIABLES	(1) Product Patents, Cat 1	(2) Product Patents, Cat 2	(3) Product Patents, Cat 3
ln(Export value)	0.175***	0.149**	0.174***
	(0.0592)	(0.0596)	(0.0660)
Number of Process Patents, Cat 1	0.00641***		
	(0.000855)		
Number of Process Patents, Cat 2		0.00364***	
		(0.000402)	
Number of Process Patents, Cat 3			0.00614***
			(0.000636)
Observations	2,231	2,279	2,259
Number of twfirm_stockID	218	223	221
Firm Fes	YES	YES	YES

Standard errors in parentheses
Standard errors clustered at the product level
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Poisson with Firm Fixed Effects, Regressing the Number of Process Patents on Firm-level Offshoring, Controlling for the Number of Product Patents

	(1)	(2)	(3)
VARIABLES	**Process Patents, Cat 1**	**Process Patents, Cat 2**	**Process Patents, Cat 3**
ln(Export value)	0.0158	0.0525	0.0310
	(0.0362)	(0.0445)	(0.0374)
Number of Product Patents, Cat 1	0.00154***		
	(0.000188)		
Number of Product Patents, Cat 2		0.00125***	
		(0.000218)	
Number of Product Patents, Cat 3			0.00161***
			(0.000206)
Observations	1,409	1,599	1,508
Number of twfirm_stockID	139	157	148
Firm FEs	YES	YES	YES