The Impact of Trade and Technology Adoption on Production Flexibility in Canadian Manufacturing

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Abstract: We exploit data on productivity, scale of operation and product diversification for Canadian manufacturing plants to investigate scale and scope economies. We find that plants face the following trade-off in their choice of production technology: higher output is generally associated with increased productivity, but larger product variety with lower productivity. The nature of this trade-off is heterogeneous across plants. Situations that are characterized by a very pronounced trade-off, i.e., where both premiums are large in absolute value, we call mass production technologies; and situations where scale economies and the penalty for variety are low we call flexible production systems. Our estimates indicate that, following increased adoption of advanced technologies and in response to U.S. tariff declines, mass production technology has gained in importance. Foreign-owned plants are also found to be less flexible than Canadian-owned plants.

Key Words: productivity, economies of scale, economies of scope, product diversification

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1. Introduction

With increasing globalization of markets, Canadian firms are facing fierce and growing competition. To remain internationally competitive, on the export market or competing with imports at home, Canadian firms are expected to produce high-quality, customized goods quickly and at a reasonable cost. Adoption of advanced technologies is generally thought to be a crucial ingredient to meet this challenge. A growing literature has examined the importance of innovation and the adoption of advanced technologies to productivity growth. While the early literature often failed to find strong evidence of the anticipated link, recent firm-level studies across many countries have shown a strong link between product innovation and firm productivity, although surprisingly not between process innovation and productivity (OECD, 2009)[1].

Studies in this literature generally consider only total output or total sales when measuring productivity and do not distinguish between different products produced by the same firm or within the same plant. We propose to study the impact of the adoption of advanced technologies on product lines directly. In particular, we conjecture that some technologies are able to lower the cost of producing multiple product lines within a plant, providing an important strategic advantage—see Van Biesebroeck (2007a) for an application to the automotive industry.

This channel of cost reduction is potentially at least as important as the reduction in the level of marginal production costs for individual products. Research into indirect effects of flexibility on market structure (Eaton and Schmidt, 1994) and on competitive interaction (Norman and Thisse, 1999), suggest far-reaching and long-lasting effects. Production flexibility is further expected to interact with outsourcing decisions and product introductions, as investigated by Van Biesebroeck (2007b) in the context of the North American automotive

[1] Evidence for Canada, indicating qualified support, is surveyed in Rao, Ahmad, Horsman, and Kaptein-Russell (2002) and Globerman (2002).

industry. Because the extent of trade openness also influences firms' optimal number of product lines (see Bernard, Redding, and Schott, 2009), observed technology decisions will interact with trade exposure.

The main message is that in differentiated product industries, cost changes have the potential to have a more complex impact than simply shifting the cost-intercept down. They can change the way firms compete and how they are organized more fundamentally. The studies cited above are theoretical or limited to the automotive industry. To draw policy conclusions one would have to investigate whether these findings can be generalized for other industries, which is what we propose to do in this study.

The rest of the paper is organized as follows. In Section 2, we introduce the empirical methodology, followed by a discussion of the Canadian plant-level data in Section 3. Estimation results are in Section 4 and we collect a few conclusions in the final section.

2. Empirical Methodology

It is widely documented—and is the standard assumption in any microeconomics textbook—that manufacturing sectors tend to be subject to positive scale economies, at least over an initial range. At the same time, it makes intuitive sense that costs will be lower if an entire plant's output consists of identical products. Producing many different products side by side on the same production line has to weakly increase production costs—Van Biesebroeck (2005, 2007a) provide evidence for the automotive industry and references to evidence for other industries. Informally, we will call this latter tendency "diseconomies of scope", even though this is not quite the textbook definition, as we will keep total output constant when we introduce additional distinct products[2].

[2] Carlton and Perloff (2005) contains an extensive discussion of the cost definitions for multiproduct firms in Chapter 2.

From the Canadian Annual Survey of Manufactures (ASM) we have information on the number of products each Canadian manufacturing plant produced between 1988 and 1996 as well as its total output. For ease of measurement, we will study the impact of scale and scope of operations on costs through its dual, productivity. If a large product line is associated with higher costs, this will translate into lower productivity or lower measures of efficiency. Implicitly, we assume that the production technology can be characterized as:

$$(1)\ \text{Productivity}_{it} = \alpha_0 + \alpha_1 \text{scale}_{\text{it}} + \alpha_2 \text{scope}_{\text{it}} + \alpha_3 \text{time} + \text{controls} + \varepsilon_{it}$$

As we can calculate plant-level productivity from the information in the ASM, we can directly estimate the coefficients in equation (1). Scale will be measured by the total output of a plant and scope by the number of product lines produced within the plant.

In a general sample of manufacturing firms, the coefficient α_1 is expected to be positive. By contrast, whether the coefficient α_2 is positive or negative might vary by industry. Moreover, the sign of α_2 might even depend on the level of aggregation in the analysis. For example, if important firm-level fixed costs such as design and R&D expenditures can be spread over multiple plants, there could be economies of scope at the *firm level*, notwithstanding diseconomies of scope at the *plant level*. Thus, the finding of diseconomies of scope at the plant level for the automotive industry by, *inter alia*, MacDuffie, Sethuraman, and Fisher (1996) is not inconsistent with the finding of economies of scope at the firm level for the same industry by Friedlaender, Winston, and Wang (1983).

Technology surveys and the innovation literature conventionally draw a distinction between product and process innovations[3]. The former are usually interpreted as affecting the demand a firm faces and the latter as influencing its supply decisions through cost reductions. As such, the effects of

[3] See for example the guidelines for collecting and interpreting technological innovation data in the OECD's *Oslo Manual: The Measurement of Scientific and Technological Activities.*

product and process innovations are often analyzed independently; here we focus on process innovations. Even though an extensive product line leads to higher costs on average, technology adoption can shift that relationship. We study how scope economies are affected by the observed process technology adoption decisions.

A second factor that is expected to affect product line choice is the exposure to international trade through import competition or a firm's own export activities; see for example Baldwin and Gu (2006), Bernard, Jensen and Schott (2006), and Baldwin and Lileeva (2008). Indirectly, we should also expect trade exposure to influence technology adoption decisions through its effect on market shares, as modeled for example in Ederington and McCalman (2007). In the empirical work, we use the reduction in Canada-U.S. tariff rates following their Free Trade Agreement (FTA) to examine whether trade exposure influences the tradeoff between productivity and firm scale and scope.

We adopt two approaches to incorporate technology adoption and trade exposure in the estimation of equation (1). First, we investigate whether the scale-scope trade-off is uniform across all plants and over time. This can be accomplished easily by estimating equation (1) over different subsamples.

Previewing the results, we note that deterministically separating plants into subsamples based on several observable variables, in particular ownership and export status and the exposure to large or small tariff cuts, will lead to different coefficient estimates. In order to let the data determine which dimensions of heterogeneity across firms matter most, rather than the researcher imposing it, we use a flexible algorithm to separate firms into subsamples. To this end, we use the estimation method developed in Van Biesebroeck (2002, 2003), which allows for the presence of two different production technologies in the sample.

In an application to the U.S. automotive industry, Van Biesebroeck (2003) showed that the trend break in productivity growth in the early 1980s can be understood as plants switching between an older "mass" technology to a modern "flexible" technology. Initially, most plants used the mass technology, which is characterized by high scale economies, but which imposes a high productivity penalty if several product lines are produced in the plant—i.e. it has high diseconomies of scope. Starting in the early 1980s, new plants entered using a more flexible technology, where the diseconomy of scope penalty was reduced at the expense of lower scale economies. These entrants were predominantly Japanese-owned plants, but even continuing American-owned plants gradually switching from the mass to the lean technology, contributed positively to aggregate productivity growth.

Equation (1) is thus generalized to:

$$\text{(2)}\quad \text{Productivity}_{it} = \alpha_0 + \alpha_1 \text{scale}_{\text{it}} + \alpha_2 \text{scope}_{\text{it}} + \alpha_3 \text{time} + \varepsilon_{it}^{F} \quad \text{if } i \in \text{Flexible}$$
$$= \beta_0 + \beta_1 \text{scale}_{\text{it}} + \beta_2 \text{scope}_{\text{it}} + \beta_3 \text{time} + \varepsilon_{it}^{M} \quad \text{if } i \in \text{Mass}$$

The distinction between the mass and flexible technology can be interpreted as a basic scale-scope trade-off in production technology. Both technologies are superior in one dimension: if only a few products need to be produced, firms should exploit scale economies to the fullest and use the mass technology. However, in the automotive industry, the proliferation of different car models over time gradually increased the attractiveness of the flexible technology for more and more plants. As a result, plants gravitated over time to the flexible technology, which has lower diseconomies of scope.

The difficulty in estimating equation (2) directly is that we generally cannot observe for each observation which of the two technologies is used, and hence whether the α or the β coefficients in equation (2) apply. This problem can, however, be addressed by using the maximum likelihood estimator developed in Van Biesebroeck (2003), which integrates out the unobserved technology state *i*. The probability that a new firm enters with the mass technology is modeled as a function of a few observable variables.

In addition, at each point in time there is, for each continuing mass technology plant, a probability that it switches from the mass to the lean technology. This probability is also modeled as a function of some (potentially different) observable variables. Adoption decisions on advanced technologies or variables capturing trade exposure can be used as shifters for the probability that either technology is used when a plant enters the sample, or for the likelihood of a technology switch for continuing plants. As such, we do not need to observe the actual technology choices of plants to estimate equation (2). Instead, we infer the probability that either type of production technology is used by each plant-year observation based on the co-movements between productivity, the number of commodities produced, and total output, together with the technology and trade variables.

One benefit of this approach is that we can estimate a model that incorporates two production technologies, even for plants for which no information on advanced technology adoption is observable[4]. Note that we use the term “technology” in two ways. On the one hand, the two characterizations of productivity in equation (2) are dubbed production technologies, which can be mass or flexible. On the other hand, specific advanced technologies can be adopted and this is observable for a subset of our sample. These will be discussed in greater detail in the data section.

We also employ a second approach to incorporate technology adoption and trade exposure in the estimation of equation (1). We can model the coefficients of the scale and scope variables in equation (1) as being explicit functions of the observed technologies used by the plants. This approach is straightforward to implement, but is only possible for the limited sample of plants for which we observe technology use directly; moreover, this approach requires a lot of degrees of freedom. The implicit assumption is that economies of scope vary continuously and firms can gradually adjust their production process to match their (evolving) product line. Tariff levels or tariff reductions might also influence the scale and scope parameters as they are likely to influence other

[4] Only about 10 percent of plants with available data on output and commodities fill in the technology survey questionnaire.

unobservable aspects of a plant's operation. Such effects can easily be incorporated by modifying the definition of the scale and scope coefficients further.

(3) $$\alpha_{2i} = \alpha_{20} + \alpha_{2i} I_{ki} + \alpha_{2t} tariff_i$$

The 1993 Survey of Advanced Technologies records past adoption decisions for a list of technologies for a subset of the plants in our dataset. Merging in this technology adoption information, we can allow the coefficients *α1* and *α2* in (1) to vary with some observed technology adoption decision (*Ii*) and with the tariff faced by the firm. Equation (3) illustrates this for the scope coefficient.

3. Data

The paper uses data from three sources. The Canadian Annual Survey of Manufactures (ASM) has data on the key plant-level variables: output, employment, productivity, 4-digit Canadian Standard Industrial Classification (SIC) industry codes, export status and foreign ownership. Productivity is defined as real value added per worker, since the ASM does not collect data on capital stock or investment and thus does not allow the calculation of total factor productivity. The ASM has commodity-level information for 'long-form' plants. These plants, which typically are larger, receive an extended survey questionnaire; only for these do we have data on the number of commodities produced at the 6-digit Standard Classification of Goods (SCG) level[5]. Our sample pools data on all plants with available commodity data for the years 1988, 1993 and 1996. This gives us an unbalanced panel with 46,324 observations on 24,789 unique plants; i.e., there are fewer than two observations per plant on average.

Information on the use of advanced technologies is taken from the 1993 Survey of Innovation and Advanced

[5] The level of detail of the 6-digit SCG is about 5,000 commodities.

Technology[6]. This survey has data on plants' use of twenty two advanced technologies, which are divided into five groups: Design and Engineering (DE), Fabrication and Assembly (FA), Automated Material Handling (AMH), Inspection and Communications (IC) and the combined groups of Manufacturing Information Systems and Integration and Control (MIS). The number of plants included in this survey is much smaller than our full sample; we call this the technology sample (N=3,887)[7].

Finally, we also use industry-level information at the 4-digit 1980 Canadian SIC level on Canadian tariffs against the United States and on U.S. tariffs against Canada in 1988, 1993 and 1996. These data were created by Daniel Trefler and used in Trefler (2004)[8].

Descriptive statistics for the principle variables used to estimate equation (1), both for the full and the technology sample, are in Table 1. The average number of commodities produced per plant is similar in both samples (2.437 and 2.720 commodities respectively). Plants in the technology sample are larger and more productive, they are more likely to be foreign-controlled and are more likely to export: 32.4 percent of the plants in the technology sample are foreign-controlled, compared to 18.5 percent in the sample of all plants; and 31.7 percent of plants in the full sample and 39.4 percent of plants in technology sample are exporters.

Technology use is summarized in Table 2. There are large differences across technologies in many dimensions: popularity, size of users and numbers of commodities produced by users. DE, FA and MIS technologies are relatively popular, used by over 30 percent of plants, versus only 5.7 percent for AMH technology. Of the DE technologies, a1 (*Computer-Aided*

[6] The list of technologies surveyed is in Appendix Table A.1; the entire survey questionnaire can be found in Baldwin and Sabourin (1995).

[7] Note that the survey contains sample weights for estimation of the characteristic means of the population of manufacturing plants.

[8] We would like to thank Daniel Trefler for providing us with the detailed tariff data.

Design/Computer-Aided Engineering), is the most popular technology, used in 806, or 21 percent of observations. It is closely followed by a16 (*Programmable controller/s*), of the IC group, which is used in 804 observations. On the opposite side, only about 3 percent of observations indicate the use of a6 (*Material Working Lasers*, of the FA group) and a22 (*Artificial Intelligence* and/or *Expert Systems*, of the MIS group) technologies[9].

The average number of commodities per user is higher for IC and MIS technologies. This may indicate that these technologies increase flexibility of production. The average size of user, measured by shipments, is the largest also for IC and MIS technologies, and is the lowest for DE technologies. So the use of IC and MIS technologies might be associated with economies of scale. (Note that these relationships can be industry-specific, rather than plant-specific.) In general, at a technology level, there appears to be a positive correlation between output and the number of commodities. This makes it more difficult to distinguish which technologies are more likely to be flexible, as opposed to mass-production, using standard linear methods.

The technology survey contains the number of years in use for each technology type. Since we want to use technology information to explain the level of productivity, we only use information on technologies adopted at least three years before the year productivity was observed. This lead time should account for learning, training, and implementation effects. For observed productivity in 1988, we use data on technologies in use by 1985; for 1993 productivity we use data on technologies in use by 1990; for 1996 productivity we use data on technologies in use by 1993. Note that, in the survey, technology use accumulates over time, so plants can adopt technologies, but they cannot discard them. As a result we have the following increasing technology use rates: 28 percent of plants used at least one technology in 1988, 46.3 percent in 1993, and 54.6 percent in 1996.

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[9] Note: The MIS group includes software such as Manufacturing Information Systems and Integration and Control.

4. Estimation Results

4.1 The fundamental trade-off

Table 3 contains a first set of estimates of equation (1) on the full sample and the technology sample. It lists both results controlling for industry-specific fixed effects (at the 4-digit SIC level, which includes 235 dummies) and for plant-level fixed effects. Recall that the panel is not balanced; accordingly, approximately one third of plants that are observed only once are dropped when plant fixed effects are included.

The estimated coefficients all have the expected signs. The number of commodities is negatively related to productivity in all specifications, indicating a productivity penalty for diversification at the plant level. In contrast, the level of total shipments is positively related to productivity, which is consistent with positive scale economies.

Note that we do not want to attach any causal interpretation to these results. One should definitely not try to infer from the estimated coefficients what the expected productivity gains would be if a plant's level of operation were exogenously enlarged, or if the number of products in production were exogenously reduced.

This becomes apparent when we control for plant fixed effects—see results in column (2) of Table 3. Compared to the results with only industry fixed effects in column (1), the productivity penalty for variety becomes notably smaller. The reverse happens for the magnitude of the positive productivity premium for higher output, which increases when plant-specific productivity fixed effects are controlled for. The changes in the estimated coefficients are consistent with plants that face increasing returns to scale expanding operations, and plants facing lower than average diseconomies of scope adding new product lines.

Estimates on the technology sample are very similar in magnitude to those for the full sample. As the sample size is more than ten times smaller, it should not come as a surprise that significance levels are lower.

Because productivity is measured by value added per worker and scale by total shipments, the latter variable is endogenous by construction in equation (1). In Table 4, we report estimation results using an instrumental variable estimator for the technology sample and industry fixed effects. Output is instrumented either with the log of average output for a plant's industry,[10] the results of which are presented in column (1) of Table 4, or with a plant's own use of heat and power, results in column (2).

Using the average industry scale as the instrument, estimates of both scope and scale coefficients are remarkably similar to the original estimates in Table 3. The absolute magnitudes of both coefficients are larger, but changes are minimal. Using the cost of heat and power as instrument, both coefficients become smaller, but the principal finding survives: scale is associated with higher productivity while breadth of the product line results in a productivity penalty.

The important result is that, in all specifications, irrespective of the type of controls, the sample, and whether or not instrumental variables were used, plants face a fundamental trade-off. There are potential productivity gains from exploiting scale economies and operating at a higher level but, if this requires the introduction of additional product lines, there will be a negative counteracting force on productivity. We believe this scale-scope interaction is a fundamental trade-off that all manufacturing firms face.

4.2 Discrete technology types

We now investigate whether all plant-year observations face the same scale-scope trade-off or whether there are important heterogeneities.

[10] The average industry output for each plant is constructed as log of the sum of shipment of plants in the 4-digit SIC industry minus output of a given plant, divided by the number of plants in this industry minus one. The own output is netted out to avoid endogeneity.

The first dimensions of heterogeneity that we investigate are ownership and export status. A large literature has already documented that plants that are foreign-owned and/or are exporters are unusual in many respects: they tend to be larger, pay higher wages, use more advanced technologies, and have higher productivity levels. The results in Table 5 indicate that, for a given plant, falling into these categories (i.e., being foreign owned or being an exporter) does not translate into a monotonic relationship for the scale or scope effects on productivity. We estimated equation (1) separating the (full) sample into four mutually exclusive groups of plants: domestically-controlled non-exporters, domestically-controlled exporters, foreign-controlled non-exporters, and foreign-controlled exporters. The estimates are reported for specifications with either industry or with plant fixed effects.

First, it should be noted that, for each of the four sub-groups, and using either set of controls, the scale coefficients are estimated to be positive and the scope coefficients to be negative. The scale-scope trade-off appears to be a pervasive phenomenon.

Further, we interpret a combination of large scale and scope coefficients—in absolute value for scope—to be indicative of an inflexible production process, or mass technology. Foreign-owned plants operating only for the Canadian market (non-exporters) are found to face the highest returns to scale, but also the highest productivity penalty associated with breadth of product line. On average, these plants seem to have installed production systems that favour producing large quantities of the same product—mass technology. This observation holds using either type of controls.

For the other types of plants, the ordering depends on whether we eliminate the variation across plants—i.e., whether we include plant fixed effects or not. If we do not, foreign-owned exporters are at the other extreme of foreign-owned non-exporters. They have the lowest scale coefficients, and by far the lowest scope coefficient (in absolute value). This suggests that they have chosen an entirely different strategy, namely to set up flexible production systems that can easily accommodate additional product lines without incurring much of a productivity penalty. Perhaps they are using Canada as a more flexible production base to serve the domestic, U.S., and other markets, while their highest volume plants are located in the United States to save on transportation costs. Of course, this is little more than speculation.

The above finding seems to be at odds with those in Baldwin and Gu (2006), who found that, in response to the Canada-U.S. FTA, Canadian plants shed product lines and increased scale, which led to sizeable productivity gains. The results in Table 5, column (2), which control for plant-level fixed effects, do indicate that identifying the scale effect for foreign-owned exporters solely from plant-level changes over time does lead to a high estimate for the coefficient on scale economies.

Results in Table 5, column (2) are on the whole consistent with Canadian-owned plants enjoying less potential to realize scale economies when they expand production. This could be the result of different technology adoption decisions or inexperience in scaling up the level of operations. It could also reflect a residual difference in outlook as Canadian industries have produced for years at a lower scale and with more diverse product portfolios for the much smaller Canadian market.

Comparing Canadian-owned exporters and non-exporters, the differences are small, but we do find in both specifications that the point estimates for the scope coefficients are higher (in absolute value) for exporters, as expected. This implies that exporters should be focusing on their comparative advantage and worrying less about producing a wide range of products. At least with plant-level fixed effects included, this strategy does seem to come with higher scale economies.

Note that 'exporter' status in Table 5 does not capture the effect of the FTA per se, since this group combines new exporters (who entered export markets after 1988) with continuing exporters. We revisit the particular effect of the 1988 trade liberalization event later, when we allow the scale and scope coefficients to vary continuously. We can, however, already note that industries that received the largest tariff cuts were slightly more flexible than those that had received the lowest cuts, but the differences were small for the two groups of plants. We do not go further into those issues here as U.S. and Canadian tariff cuts should also have different effects and we can incorporate this feature later on.

We expect the scale-scope trade-off to differ across industries. For example, industries producing large varieties of complex products should have greater incentives to invest in flexible technologies to mitigate some of the scope effects. We estimated equation (1) on all 2-digit SIC industries but, to conserve space, we only indicate a few of the findings[11]. Industries that show a high penalty for product variety include *Primary Textile* SIC18*, Electrical and Electronic Products* SIC33*, Chemical Products* SIC37. The highest economies of scale are observed in *Chemical Products* SIC37, *Petroleum Products* SIC36, *Beverages* SIC11, *Rubber* SIC15 and *Wood* SIC25. Virtually all industries show a positive sign on the scale coefficient and a negative sign for scope, but the positive relationship between output and productivity tends to be far more robust.

4.3 Discrete technology types with endogenous assignment

We now estimate the model with two technology types, allowing the data to self-select into two groups, using the estimation methodology from Van Biesebroeck (2003) that was described earlier. The first time a plant is observed in the sample the algorithm assigns a probability that the production technology is of the old type (with one minus that probability being assigned to the new technology type). Going forward, a second probability applies which determines the likelihood that plants still using the old technology are updating to the new one. While we do not observe the actual production technologies used, we rely on observable variables to parameterize the two probabilities, which together imply a probability for both technologies for each plant at each point in time. In the algorithm, the new technology is an absorbing

[11] The complete set of estimates is available upon request.

state—i.e., once a plant adopts the new technology, it will not subsequently switch to the alternative technology. We do not impose any restrictions on the nature of the scale-scope trade-off for the two technologies.

Two questions are important. First, do both technologies have the characteristics illustrated in Tables 3, 4, and 5 of positive scale and negative scope economies? Second, if one of the two technologies can be characterized as more flexible—i.e. has lower absolute values of both the scale and scope coefficients—is it the new or the old technology?

In the results presented in Table 6, the initial probability of a plant using the new technology is modeled as a function of a year trend and the foreign ownership dummy. As foreign-controlled plants have easier access to new technologies, they might be more likely to operate with the new technology, and thus not be open to the possibility of a technology switch. On the other hand, Canadian-controlled plants are more likely to focus on the domestic market and to produce a greater variety of products, which would favour the flexible technology, be it the old or new one.

As in Van Biesebroeck (2003), we use the average number of commodities produced by competitors to predict the probability of technology switching. This variable should be a good predictor for the demand for the comparative advantage of the new technology, be it higher scale or scope economies.

The results of this non-linear maximum likelihood estimation are presented in Table 6. Both scale coefficients are estimated to be positive and both scope coefficients to be negative, indicating that both technologies are characterized by the same scale-scope trade-off as before[12].

[12] Note that the coefficients of the old technology are estimated directly, and reported in column (1) of Table 6, while the coefficients of the new technology are calculated as the sum of the old technology coefficients and two difference coefficients. The latter are estimated directly and results are reported in column (2). As a result, no t-statistic for the new technology coefficients in column (3) are reported, but the very high t-statistics on the difference coefficients indicate that the scale and scope effects are significantly different for the two technologies.

The estimates indicate very starkly that the 'old' production technology is the one characterized by greater flexibility. The productivity penalty for variety increases tremendously, from -0.077 to -0.785, for the new technology. The advantage of the new technology is a corresponding increase in the scale effect, with a coefficient on total shipments of 0.498, more than double the 0.226 estimate for the old technology.

The estimates on the parameters governing the probabilities for either technology (not presented) suggest that the likelihood of new plants entering with the mass technology increases over time; although the increase is not statistically significant. If plants change their operations, switches tend to make the production technology less flexible, but with higher scale effects.

The finding of plants switching towards the mass technology differs from the pattern observed for the U.S. automotive industry, but it is a plausible response to the Canada-U.S. FTA. As a result of the FTA, Canadian plants obtained easier access to the much larger U.S. market, which is consistent with the finding in Table 6 that over time they become more likely to choose the technology with the highest scale economies. The finding is also consistent with the FTA-induced increase in specialization of production found by Baldwin and Gu (2006). They found that tariff cuts reduced product diversification and increased production runs for exporters, which should be expected to focus on a few comparative advantage products. For non-exporters, tariff cuts are also found to reduce product diversification, which is consistent with the greater domestic competition they are facing from U.S. firms.

4.4 A continuum of production technologies

The final step in our analysis is to analyze what the patterns in the productivity distribution look like, if we allow the scale and scope parameters to vary continuously as a function of observed technology adoption decisions. This analysis can only be conducted on the limited technology sample, because only for those plants do we observe technology use directly. As a robustness check, we allow the coefficients on scale and scope to vary with the Canadian and U.S. import tariffs, as in equation (3). The latter regression can be estimated on the full sample. Plants that are subject to greater import competition or enhanced export opportunities will have different demands for technology to boost their potential scale and/or scope economies; this should show up in the coefficient estimates.

For the technology sample, we have information on the use of twenty-two advanced technologies—the full list is in the Appendix. Some of these technologies could reduce the productivity penalty associated with product variety, while some others could even increase them. There is no way for us to determine *a priori* the expected effect of each technology based on its description—although the patterns in Table 2 provide some hints.

For simplicity, we create an aggregated binary variable, which equals one if any of the twenty-two advanced technologies is adopted, and zero otherwise. We then estimate equation (1) for the technology sample, allowing for interaction between technology use and the scale and scope variables. The estimates are reported in the top panel of Table 7 for the entire technology sample.

With either industry or plant fixed effects, technology adoption is found to be related to higher returns to scale. We already know from the summary statistics in Table 2 that large firms are a lot more likely to adopt advanced technologies; nonetheless, the estimate in Table 7 indicates that this does not mean that they have exploited all scale economies. On the contrary, advanced technology use is associated with higher scale economies even if the adopting plants are larger. Note that the direction of causality could go either way. It could be that new technologies boost scale economies, but it might just as well be that firms facing higher scale economies are upgrading their technologies most rapidly.

The coefficient on the interaction between technology use and the number of commodities, "Scope x Technology", is estimated to be negative with either set of controls; the effect is especially important in the specification with plant fixed effects.

When plants increase the number of commodities and at the same time adopt new technologies, their productivity takes a large hit. We find that technology adoption is more prevalent for inflexible mass technology plants that face scale economies; interpreted differently, new technologies tend to make the production technology less flexible[13].

We estimated the same specification separately for two groups of industries, which are sorted based on the extent of tariff cuts in the Canada-U.S. FTA. The results in panels (b) and (c) of Table 7 demonstrate that the above effects are driven by industries that experienced large tariff cuts. For industries that experienced small cuts, the interaction terms between technology and the scale and scope effects are always insignificant. For industries subject to large tariff cuts, the association between technology adoption and inflexible production becomes even stronger.

We next seek to evaluate the impact of the individual twenty-two technologies on production flexibility by including a full set of technology use dummies and interactions between their use and the scale and scope variables. Unfortunately, this analysis is complicated by serious multicollinearity; the vast majority of the coefficients on the interaction terms are not statistically significant.

One promising line of future research on this issue is to use factor analysis to reduce the dimensionality of the technology adoption decision. We found that 74 percent of the variation in adoption rates is explained by a single factor, and 90 percent by the first two factors. The first factor puts non-zero weights on most technologies, but the highest weight falls on technologies a16 and a17 from the *Inspection and Communications* group, and technologies a18 and a21 from *Manufacturing Information Systems* group[14]. In follow-up work, we plan to estimate

[13] Distinguishing between these two causal interpretations is beyond the scope of this paper.

[14] The second factor explains 15 percent of variation, but places substantial weights only on 5 technologies (four of which are from the *Design and Engineering Group*).

equations (1) and (3) using just the first two factors as interaction terms for the scale and scope variables.

Finally, we take a closer look at the direct impact of tariff cuts. In the full sample, we include Canadian and U.S. tariffs into equation (1), as well as interactions between tariffs and output, and tariffs and the numbers of products, as in equation (3). As we use actual tariff levels, low values of the tariff variables indicate liberalized trade. Over time, tariff levels have come down; in 1996, most tariffs were at or very close to zero.

The results in Table 8 for the specification with only industry fixed effects yields mostly insignificant results; accordingly, we focus on the results for the specification with plant-level fixed effects. The estimates on the uninteracted tariff variables in column (2) imply that plants in industries initially protected by high Canadian tariffs had on average higher productivity growth, while those facing higher U.S. tariffs had lower growth. Viewed differently, plants in industries where Canadian tariff concessions were large enjoyed on average higher rates of productivity growth—potentially due to stronger competition post-FTA.

Interacting the U.S. tariff with the variables of interest yields a very small point estimate for the impact on labour productivity of increased scope which is not significantly different from zero. The interaction with scale, on the other hand, exerts a large, positive, and statistically very significant impact on labour productivity. This may reflect the presence of large potential scale economies for plants that initially faced higher U.S. tariffs. When export opportunities to the United States opened up, plants either invested in new technology needed to access these potential scale economies or—more plausibly in our view—simply expanded output, exploiting and exhausting the scale economies that their existing technologies provided.

The reverse was taking place on the domestic Canadian market. Plants in industries where Canadian tariffs declined significantly saw their available scale economies grow. A plausible explanation is that competition from expanding U.S. imports reduced the *actual* scale of operations of many domestic plants, which would imply increased available *potential* scale economies, if production technology did not adjust. An additional finding for these industries is that the coefficient on the interaction between the Canadian tariff level and the number of commodities is negative. Initially, when tariffs were high, there were sizeable diseconomies of scope, but as tariffs declined to zero, these diseconomies disappeared. Canadian plants seem to have adjusted to trade liberalization by making their production process more flexible and by reducing the productivity penalty associated with a large product portfolio. Another process that might have contributed to the observed pattern is that these plants cut product lines and the lower diversification brought their product portfolio back into an area where they could more efficiently handle the variety.

5. Conclusion

The results indicate that Canadian manufacturing plants face a trade-off in terms of productivity: higher output increases productivity, but a larger product variety reduces it. No matter how one cuts the data, this pattern is robust, but the productivity premium for scale and the penalty for variety does vary across plants.

We can discern situations where both premiums are large in absolute value, which we call mass production or inflexible plants. In other situations, which we call flexible production technologies, both premiums are low indicating low returns to scale, but also lower diseconomies of scope. Either technology can be ideal for a plant, depending on its scale of operation and production mix. For example, we find that foreign-controlled plants that do not export seem to choose the least flexible technology, i.e. have the highest productivity premiums on both scale (positive) and scope (negative).

We estimated a model that allows for two parameterizations of the scale-scope trade-off in the production technology available to plants in our sample. The estimation algorithm lets the data decide which technology is most appropriate for each plant-year observation and incorporates one-way technology switching. The two technologies thus estimated can clearly be identified as one mass and one flexible technology.

Our results suggest that the mass technology is gaining in importance over time. The exploitation of higher scale economies seems to have become more valuable over time than maintaining production flexibility.

When we allow the scale and scope premiums to vary continuously with technology adoption and tariff rates, similar conclusions emerge. Technology adoption is associated with less flexible production, especially for plants in industries that saw large tariff cuts as a result of the Canada-U.S. FTA. In particular, the reduction of U.S. tariffs is associated with a decrease in available scale economies, consistent with the large expansion in output by Canadian exporters. The reduction of Canadian import tariffs, on the other hand, has the reverse effect on scale economies for import-competing industries, but it also reduced the productivity penalty associated with product variety in those industries—either due to operational changes or due to the elimination of product lines.

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Table 1: Descriptive Statistics

	MEAN	STD	MIN	MAX
	Full sample[1], N=46,324			
Log of productivity	10.952	0.759	2.526	18.759
Number of commodities	2.437	2.109	1.000	33.000
Log of no. of commodities	0.660	0.634	0.000	3.497
Log of shipments	15.189	1.800	8.854	23.575
Foreign-control dummy	0.185	0.388	0.000	1.000
Export status dummy	0.317	0.465	0.000	1.000
	Technology sample[2], N=3.887			
Log of productivity	11.160	0.791	4.920	16.532
Number of commodities	2.720	2.671	1.000	33.000
Log of no. of commodities	0.727	0.689	0.000	3.497
Log of shipments	16.115	1.687	10.309	21.637
Foreign-control dummy	0.324	0.468	0.000	1.000
Export status dummy	0.394	0.489	0.000	1.000

Notes:

1. All plants in the ASM with available commodity data for 1988, 1993 and 1996.
2. Plants that were both in the ASM with available commodity data for 1988, 1993 and 1996, and in the 1993 Survey of Innovation and Advanced Technology.

Table 2: Technologies Adoption Rates (Technology Sample, N=3,887)

	MEAN	SE		MEAN	SE	No. of Adopters	Average No. of Commodities	Average shipments of adopters
DE	0.360	0.480	a1	0.334	0.472	806	2.78	91,853,924
			a2	0.121	0.326	294	2.83	70,004,980
			a3	0.070	0.255	148	2.81	92,429,905
FA	0.252	0.434	a4	0.076	0.266	180	2.68	146,984,000
			a5	0.175	0.380	512	2.55	59,700,646
			a6	0.028	0.165	72	2.60	145,206,917
			a7	0.054	0.226	130	2.38	175,467,823
			a8	0.053	0.224	138	2.43	111,251,007
AMH	0.057	0.232	a9	0.057	0.232	165	2.98	102,421,818
			a10	0.000	0.000	55	2.85	149,016,473
IC	0.398	0.490	a11	0.091	0.288	255	3.40	187,672,427
			a12	0.118	0.322	332	3.14	180,070,018
			a13	0.169	0.375	369	2.97	146,316,293
			a14	0.134	0.340	303	3.21	154,873,426
			a15	0.112	0.315	240	3.38	125,131,825
			a16	0.277	0.447	804	3.10	119,722,148
			a17	0.232	0.422	624	3.13	136,557,646
MIS	0.308	0.462	a18	0.220	0.415	577	3.11	118,056,711
			a19	0.127	0.333	307	3.21	148,108,186
			a20	0.089	0.284	233	2.87	132,275,386
			a21	0.134	0.340	351	3.26	179,371,903
			a22	0.032	0.177	73	3.32	135,253,575

Notes:

1. Average shipments of adopters is in current Canadian dollars.
2. The MIS group includes software such as Manufacturing Information Systems and Integration and Control.

Table 3: Impact of Scale and Scope on Plant Productivity

	Dependent variable is the log of labour productivity			
	Estimate	t-statistic	Estimate	t-statistic
	(1)		(2)	
Fixed effects:	Industry		Plant	
Full Sample, N=46,324				
Scope	-0.091	(18.48)	-0.025	(-2.86)
Scale	0.220	(114.26)	0.428	(55.28)
Year1993	0.153	(20.20)	0.114	(16.64)
Year1996	0.202	(26.80)	0.106	(14.50)
Technology Sample, N=3,887				
Scope	-0.117	(-6.97)	-0.051	(-1.94)
Scale	0.229	(28.91)	0.537	(21.88)
Year1993	0.145	(5.99)	0.110	(5.61)
Year1996	0.196	(7.90)	0.096	(4.45)

Note: Estimates of equation (1). Scope is measured by the log of number of commodities; scale by the log of shipments

Table 4: Estimates of Scale and Scope Effects using Instrumental Variables, Technology Sample, N=3,887

	Dependent variable is the log of labour productivity			
	Estimate	t-statistic	Estimate	t-statistic
	(1)		(2)	
Fixed effects:	Industry		Plant's own	
Instruments	Mean industry-level scale		Heat & power expenditure	
Scope	-0.124	(-7.14)	-0.087	(-5.00)
Scale	0.248	(17.19)	0.151	(15.01)

Note: Estimates of equation (1) using instrumental variables for scale (total shipments). Variables are measured as in Table 3 and year dummies are included, but coefficient estimates not reported.

Table 5: Estimates of the scale-scope trade-off for different types of plants (Full sample)

		Dependent variable is the log of labour productivity				
		Estimate	t-statistic	Estimate	t-statistic	N
		(1)		(2)		
Fixed Effects		Industry		Plant		
Domestic-owned, Non-exporters	Scope	-0.080	(-10.90)	-0.026	(-1.63)	24,488
	Scale	0.220	(73.94)	0.413	(30.72)	
Domestic-owned, Exporters	Scope	-0.097	(-12.12)	-0.030	(-1.73)	13,289
	Scale	0.205	(47.98)	0.442	(26.51)	
Foreign-owned, Non-exporters	Scope	-0.163	(-7.58)	-0.058	(-1.34)	3,602
	Scale	0.255	(22.80)	0.570	(17.67)	
Foreign-owned, Exporters	Scope	-0.048	(-3.34)	-0.043	(-1.56)	4,945
	Scale	0.197	(24.82)	0.523	(20.25)	

Notes: OLS estimation results for equation (1), with firms split in four mutually exclusive categories. Year dummies included as controls.

Table 6: Nonlinear Estimation of Two Technologies with Technology Switching (Technology sample, N=3,887)

	Dependent variable is labour productivity				
	Old technology		Difference		New technology
	Estimate	t-statistic	Estimate	t-statistic	Implied Estimate
	(1)		(2)		(3)
Scope	-0.077	(-6.47)	-0.708	(-3.68)	-0.785
Scale	0.226	(46.04)	0.272	(3.85)	0.498

Note: Maximum likelihood estimation of the coefficients on the old technology, column (1), and the difference between the coefficients of the old and new technologies, column (2). The implied estimates for the coefficients on the new technology are in column (3). The old technology is the one that plants can still switch out of.

Table 7: Scale-scope Trade-off with Coefficients Varying with Technology Use

	Dependent variable is log of labour productivity			
	Estimate	t-statistic	Estimate	t-statistic
	(1)		(2)	
Fixed effects:	Industry		Plant	
(a) Entire technology sample (N = 3,887)				
Scope	-0.110	(-5.08)	-0.015	(-0.48)
Scale	0.218	(20.87)	0.512	(18.99)
Technology use	-0.627	(-2.72)	-0.818	(-2.13)
Scope x Technology	-0.019	(-0.61)	-0.080	(-2.15)
Scale x Technology	0.037	(2.59)	0.053	(2.25)
(b) Industries with large tariff cuts (N = 2,242)				
Scope	-0.098	(-3.44)	-0.006	(-0.14)
Scale	0.213	(16.23)	0.532	(14.96)
Technology use	-1.259	(-4.11)	-1.024	(-2.06)
Scope x Technology	-0.064	(-1.62)	-0.116	(-2.35)
Scale x Technology	0.077	(4.05)	0.066	(2.19)
(c) Industries with small tariff cuts (N = 1,453)				
Scope	-0.140	(-4.04)	-0.033	(-0.66)
Scale	0.234	(13.27)	0.458	(10.02)
Technology use	0.182	(0.49)	-0.719	(-1.11)
Scope x Technology	0.072	(1.43)	-0.019	(-0.31)
Scale x Technology	-0.017	(-0.73)	0.042	(1.06)

Table 8 Scale-scope Trade-off as a Function of Canadian and U.S. Tariffs (full sample)

	Dependent variable is log of labour productivity			
	Estimate	t-statistic	Estimate	t-statistic
	(1)		(2)	
Fixed effects:	Industry		Plant	
Scope	-0.078	(-12.89)	-0.010	(-1.00)
Scale	0.220	(97.62)	0.428	(53.05)
Tariff into Canada (TC)	-0.504	(-0.52)	5.159	(3.40)
Scope x TC	-0.134	(-0.82)	-0.356	(-1.83)
Scale x TC	0.010	(0.17)	-0.321	(-3.39)
Tariff into U.S. (TUS)	1.913	(0.97)	-7.606	(-2.39)
Scope x TUS	-0.338	(-1.21)	0.018	(0.05)
Scale x TUS	-0.088	(-0.72)	0.448	(2.24)

Appendix

Table A.1 List of advanced manufacturing technologies

Code	Description
Design and Engineering	
A1	Computer aided design (CAD) and /or Computer aided engineering (CAE)
A2	CAD output used to control manufacturing machines (CAD/CAM)
A3	Digital representation of CAD output used in procurement activities
Fabrication and Automation	
A4	Flexible manufacturing cell(s) (FMC) or systems (FMS)
A5	Numerically controlled and computer numerically controlled machines
A6	Material working laser(s)
A7	Pick and place robots(s)
A8	Other robots
Advanced Material Handling	
A9	Automated storage and retrieval systems (AS/RS)
A10	Automated guided vehicle systems (AGVS)
Inspection and Communications	
A11	Automated sensor-based equipment used for inspection/testing of incoming or in-process materials
A12	Automated sensor-based equipment used for inspection/testing of final product
A13	Local area network for technical data
A14	Local area network for factory use
A15	Inter-company computer network linking plant to subcontractors, suppliers and/or customers
A16	Programmable controller(s)
A17	Computer(s) used for control on factory floor
Manufacturing Information Systems	
A18	Material requirement planning (MRP)
A19	Manufacturing resource planning (MRP II)
Integration and Control	
A20	Computer integrated manufacturing (CIM)
A21	Supervisory control and data acquisition (SCADA)
A22	Artificial intelligence and/or expert systems