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Multiple-Product Firms and Product Switching

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This paper examines the frequency, pervasiveness, and determinants of product switching by US manufacturing firms. We find that one-half of firms alter their mix of five-digit SIC products every five years, that product switching is correlated with both firm- and firm-product attributes, and that product adding and dropping induce large changes in firm scope. The behavior we observe is consistent with a natural generalization of existing theories of industry dynamics that incorporates endogenous product selection within firms. Our findings suggest that product switching contributes to a reallocation of resources within firms toward their most efficient use. (*JEL* L11, L21, L25, L60)

The extent to which resources are allocated to their best use is a core issue of economics. Until now, research into industry dynamics has addressed this issue by focusing almost exclusively on the contribution of firm entry and exit to resource reallocation, that is, whether newly created firms or plants are more productive than the dying firms and plants they replace.[1] This paper examines a new, "extensive" margin of firm adjustment, the reassignment of resources that takes place within surviving firms as they add and drop (i.e., "switch") products.

Our analysis of product switching makes use of a unique longitudinal dataset that tracks US firms' product-level manufacturing output across quinquennial US Manufacturing Censuses from 1987 to 1997. In this dataset, a "product" is one of approximately 1,500 five-digit Standard Industrial Classification (SIC) categories, e.g., "Passenger Cars."[2] We observe the set of products each manufacturing firm produces in each census year and analyze how incumbent firms' mix of products evolves from one census year to the next. To our knowledge, these are the most

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[1] There is a large empirical literature in macroeconomics on firm creation and destruction and its implications for industry dynamics and the firm-size distribution. See, for example, Martin N. Baily, Charles Hulten, and David Campbell (1992), Timothy Dunne, Mark J. Roberts, and Larry Samuelson (1989a, b), Lucia Foster, John Haltiwanger, and C. J. Krizan (2001), Foster, Haltiwanger, and Chad Syverson (2008), and Esteban Rossi-Hansberg and Mark J. Wright (2007) among others.

[2] We refer to two-, four- and five-digit SIC categories as "sectors," "industries," and "products," respectively.

comprehensive data on multiple-product production yet assembled. Standard manufacturing censuses, for example, typically record just the primary industry of each establishment.[3]

We find product switching to be frequent, widespread, and influential in determining both aggregate and firm outcomes. On average, recently added and about-to-be dropped products each account for roughly one-sixth of a product's output, amounts that rival the shares represented by recently created and about-to-exit firms. At the firm level, we find that more than one-half of US manufacturing firms alter their mix of products between censuses, and that one-half of those firms change their mix of products by *both* adding and dropping at least one product every five years. Product adding and dropping also exert considerable influence on the scope of firms, with an average of 40 percent of firms adding products outside their existing set of four-digit SIC industries between census years. Given the unobserved changes firms presumably make to their product mix at lower levels of aggregation, our estimates of product switching likely underestimate the true importance of firms' adjustments to their extensive margins.[4]

Our empirical analysis is guided by a model of endogenous product selection that builds on existing theories of industry dynamics by Boyan Jovanovic (1982); Hugo A. Hopenhayn (1992); Richard Ericson and Ariel Pakes (1995); Marc J. Melitz (2003); and Bernard, Redding, and Schott (2007).[5] In these existing models, firms that are heterogeneous in productivity are assumed to produce a single product, with the result that firm and product-market entry and exit are equivalent. Here, we develop a natural extension of such models in which firms choose to produce an endogenous range of products in response to evolving firm and firm-product characteristics.[6] In our model, firms differ in innate productivity while firms' products vary in their attractiveness to consumers vis-à-vis other producers of the same product. The overall profitability of a firm depends on the interaction of these attributes. Higher values of consumer tastes for a firm's product raise the firm's profitability in that product, while higher values of firm productivity increase a firm's profitability in *all* products. In equilibrium, the most productive firms manufacture the largest ranges of products because they earn greater revenue per product for given values of consumer tastes, and can therefore cover the fixed costs of a wider set of products.

Our framework provides a basis for understanding many of the empirical regularities discernible in US census data. In the data, we find that multiple-product firms have higher measured revenue-based productivity than single-product firms. In the model, this difference is due to high-productivity firms' ability to cover the fixed costs of a greater number of products. In the data, we find product switching and firm creation and destruction to be commonplace and

[3] Existing empirical work on multiple-product firms typically examines product diversification at a point in time. See, for example, Frank M. Gollop and James L. Monahan (1991) and John Baldwin and Wulong Gu (2009). Dunne et al. (1988, 1989b) examine product diversification as a mode of market entry distinct from plant birth, while Dunne, Shawn D. Klimek, and Roberts (2005) investigate the empirical relationship between the mode of market entry and plant death.

[4] One of the attractions of our data is that information is available for the entire manufacturing sector. Scanner data, such as those used by Judith A. Chevalier, Anil K. Kashyap, and Peter E. Rossi (2003) and Christian Broda and David E. Weinstein (2007), offer the potential to measure products at finer levels of disaggregation, although they are typically available only for specific categories of goods.

[5] These models receive empirical support from studies of firm creation and destruction by Baily et al. (1992), Dunne et al. (1989a, b) and Foster et al. (2001, 2008).

[6] Existing theoretical research on multiple-product firms focuses on issues associated with managing a given range of products at a particular point in time, e.g., William J. Baumol (1977); John C. Panzar and Robert D. Willig (1977); James A. Brander and Jonathan Eaton (1984); Avner Shaked and John Sutton (1990); and B. Curtis Eaton and Nicolas Schmitt (1994). More recently, Tor Jakob Klette and Samuel Kortum (2004); Erzo G. J. Luttmer (2008); and Satyajit Chatterjee and Rossi-Hansberg (2008) have explored the role of innovation in determining firm scope, as discussed further below.

pervasive across sectors. In the model, interactions of stochastic shocks to firm productivity and stochastic shocks to consumer tastes foster steady-state product adding and dropping, as well as steady-state firm creation and destruction. In the data, we observe a positive correlation between products' add and drop rates. In the model, this correlation arises because firms that receive positive demand shocks add the product at the same time that some incumbent producers drawing negative demand shocks drop it. In the data we find that the probability that a firm drops a product declines with firm-product shipments and firm-product tenure. In the model, this scale and age dependence arises as a result of serial correlation in idiosyncratic shocks to firm-product profitability. Firms' lower-volume and recently added products are more likely to be dropped as a result of a negative shock.

Our results also emphasize the central role of the firm in mediating product adding and dropping. In the data, we find that product adding is positively correlated with firms' measured revenue productivity, and that product dropping is influenced by firm as well as firm-product attributes. In the model, decisions to add or drop products are interdependent, given the contribution of the firm-level productivity draw to the profitability of all of a firm's products. We also find product switching to be related to firm outcomes, with net adding and net dropping of products being positively and negatively correlated with measured revenue productivity, respectively. In the model, such contemporaneous responses are driven by shocks to productivity: firms receiving positive shocks earn greater revenue per existing product and expand, while firms receiving negative shocks contract.

Though our model serves as a useful guide for our empirical analysis, in its current form it is too stylized to provide an explanation for all of the facts that we uncover. We find, for example, that some pairs of products are more likely to be coproduced within firms than others, and that mergers and acquisitions account for a relatively small share of the number of products added and dropped, but a larger share of their value. While these facts transcend our basic setup, we describe how the model might be extended to incorporate them.

The remainder of the paper is structured as follows. Sections I and II outline our theoretical framework and describe our dataset. Sections III and IV report our main empirical findings and their consistency with our theoretical framework. Section V concludes, with suggestions for future research.

I. Theoretical Framework

In this section we outline a simple model of multiple-product firms and product switching that is a natural extension of standard models of industry dynamics by Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995), Melitz (2003), and Bernard, Redding, and Schott (2007). Our goal is to introduce the simplest model necessary for useful data analysis, i.e., one that captures the essence of a broad class of models featuring product selection. Toward that end, we employ a number of simplifying assumptions, for example, ruling out supply- or demand-driven complementarities across products. We return to a discussion of how the model might be generalized, and discuss alternative potential approaches after presenting our main empirical findings. We note that a more detailed discussion of the model and a more formal analysis of its implications are available in a Web Technical Appendix.[7]

[7] Available from http://www.aeaweb.org/articles.php?doi=10.1257/aer.100.70.

A. *Endowments and Preferences*

Labor is the sole factor of production and is assumed to be in inelastic supply L (which also indexes the size of the economy). The representative consumer's preferences are a constant elasticity of substitution (CES) function of the consumption of a continuum of products $i \in [0, 1]$:

$$(1) \qquad U = \left[\int_0^1 (a_i C_i)^\nu \, di \right]^{\frac{1}{\nu}}, \qquad 0 < \nu < 1,$$

where $a_i > 0$ is a demand parameter that allows the relative importance of products in utility to vary. Firms are assumed to produce differentiated varieties of products, so that C_i is a consumption index, which also takes the CES form

$$(2) \qquad C_i = \left[\int_{\omega \in \Omega_i} (\lambda_i(\omega) c_i(\omega))^\rho \, d\omega \right]^{\frac{1}{\rho}}, \quad P_i = \left[\int_{\omega \in \Omega_i} \left(\frac{p_i(\omega)}{\lambda_i(\omega)} \right)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}}, \quad 0 < \rho < 1,$$

where ω indexes firm varieties within products, Ω_i is the (endogenous) set of firm varieties produced within product i, and P_i is the price index dual to C_i for product i.

The demand parameter $\lambda_i(\omega) \geq 0$ determines the representative consumer's relative demand for the varieties of different firms within each product.[8] Although not central to our results, we make the natural assumption that the elasticity of substitution across varieties within products is greater than the elasticity of substitution across products: $\sigma = 1/(1 - \rho) > \kappa = 1/(1 - \nu) > 1$. Similarly, we assume for simplicity that the elasticity of substitution across varieties within products, $\sigma = 1/(1 - \rho)$, is the same for all products.

B. *Production Technology*

Firms from a competitive fringe may enter by incurring a sunk entry cost of $f_e > 0$ units of labor. Incurring the sunk entry cost creates a firm brand and a blueprint for one horizontally differentiated variety of every product. Only once the sunk cost has been incurred does the firm observe its initial productivity, $\varphi \in [\underline{\varphi}, \overline{\varphi}]$, and consumer tastes for the characteristics embodied in its blueprint for every product, $\lambda_i \in [\underline{\lambda}, \overline{\lambda}]$. Productivity φ is firm-specific but is common across products within firms, whereas consumer tastes λ_i are firm-product specific and are therefore idiosyncratic to a particular product made by a particular firm.[9]

Productivity and consumer tastes evolve stochastically over time and we choose a specification for their evolution that is both tractable and sufficiently general to match key features of the firm-product data.[10] Upon entry, productivity and consumer tastes are drawn from the continuous distributions $g_e(\varphi)$ and $z_{ei}(\lambda_i)$, respectively, with cumulative distributions $G_e(\varphi)$ and $Z_{ei}(\lambda_i)$. Once a firm observes its initial values of productivity and consumer tastes, it decides whether

[8] One interpretation of the parameter $\lambda_i(\omega)$ is product quality, though this parameter also captures other more subjective characteristics of a firm's variety that influence consumer tastes.

[9] With CES demand and monopolistic competition, differences in productivity across firms have identical effects on equilibrium revenue and profits to differences in consumer tastes. While we have modeled the component of profitability that is firm-product specific (λ_i) as consumer tastes, we could have equivalently introduced a productivity parameter that is firm-product specific. While consumer tastes are a plausible source of idiosyncratic shocks to firm-product profitability, the important point for our analysis is that the profitability of a product for a firm has both a firm and a firm-product component.

[10] Bernard, Redding, and Schott (2006) introduce a static model of multiproduct firms without equilibrium product switching to examine the impact of trade liberalization on firms' product scope.

to produce or exit. If the firm exits, its production knowledge is lost, and the sunk cost must be incurred again in order for the firm to reenter. If the firm enters, it faces a Poisson probability $\theta > 0$ of a shock to productivity φ, in which case a new value for productivity φ' is drawn from the continuous conditional distribution $g_c(\varphi' | \varphi)$, with cumulative distribution $G_c(\varphi' | \varphi)$. Similarly, the firm faces a Poisson probability $\varepsilon_i > 0$ of an idiosyncratic shock to consumer tastes for its variety λ_i, in which case a new value for consumer tastes λ_i' is drawn from a continuous conditional distribution $z_{ci}(\lambda_i' | \lambda_i)$, with cumulative distribution $Z_{ci}(\lambda_i' | \lambda_i)$.[11]

Consistent with the serial correlation in firm and firm-product shipments observed in our data, we assume that consumer tastes and productivity are positively serially correlated, which corresponds to the following assumption about their conditional distributions: $\partial Z_{ci}(\lambda_i' | \lambda_i)/\partial \lambda_i < 0$ and $\partial G_c(\varphi' | \varphi)/\partial \varphi < 0$ for $\lambda_i' \in [\underline{\lambda}, \overline{\lambda}]$ and $\varphi' \in [\underline{\varphi}, \overline{\varphi}]$. Thus the probability of drawing a new value for consumer tastes (productivity) less than λ_i' (φ') is decreasing in the existing value of consumer tastes (productivity). To make use of law of large numbers results, we assume that the distributions of consumer tastes and productivity are independent across firms. For the same reason, we also assume that the distributions of consumer tastes are independent across products and that the distributions of consumer tastes and firm productivity are independent of one another.[12] Firms also face a Poisson probability of death $\delta > 0$ due to *force majeure* events unrelated to profitability.

The production technology takes the following form. There is a fixed corporate headquarters cost of $f_h > 0$ units of labor, which the firm must incur irrespective of the number of products that it chooses to produce, and a fixed production cost of $f_{pi} > 0$ units of labor for each product i that is produced. In addition, there is a constant marginal cost for each product, which depends on the firm's productivity. Total labor employed by a firm with productivity φ is thus

$$l(\varphi) = f_h + \int_0^1 I_i \left[f_{pi} + \frac{q_i(\varphi, \lambda_i)}{\varphi} \right] di, \tag{3}$$

where I_i is an indicator variable that equals one if a firm produces product i and zero otherwise, and $q(\varphi, \lambda_i)$ denotes output of product i by a firm with productivity φ and demand λ_i.

C. *Equilibrium Entry and Production Decisions*

The key economic decisions of a firm in the model are whether to enter or exit and in which product markets to participate. We begin by considering the decision of whether to participate in a product market. If a firm produces a product, it supplies one of a continuum of varieties each with measure zero relative to the product market as whole. As this is true for each of the continuum of products, the firm's profit maximization problem reduces to choosing the price of each product variety separately to maximize the profits derived from that product variety. This optimization problem yields the standard result that the equilibrium price of a product variety is a constant mark-up over marginal cost:

$$p_i(\varphi, \lambda_i) = \frac{1}{\rho} \frac{w}{\varphi}, \tag{4}$$

[11] While the model could be extended to allow firms to make endogenous investments in improving productivity and enhancing consumer tastes, these extensions are not central to the model's key predictions, which are driven by selection, and so we do not pursue them here.

[12] While the consumer taste and firm productivity distributions are independent of one another, there is interdependence in a firm's profitability across products, because firm productivity is common across products. In Section IV below, we discuss extending the model to introduce other forms of interdependence.

where we choose the wage for the numeraire and so $w = 1$.

Under our assumption of CES preferences, equilibrium prices are inversely related to firm productivity. As φ rises, variable labor input and output rise, but prices fall, leaving revenue per variable input unchanged. Nevertheless, the model features dispersion in revenue-based measures of productivity across firms, as examined in our empirical analysis below, because of the assumption of fixed production costs. As φ rises, variable labor input and revenue increase, with the result that the fixed labor input is spread over more units of revenue.[13]

As there is a fixed production cost for each product, there exists a *zero-profit consumer taste cutoff* $\lambda_i^*(\varphi)$ such that a firm with productivity φ will produce product i only if it draws a consumer taste greater than or equal to $\lambda_i^*(\varphi)$. The zero-profit consumer taste cutoff is defined as follows:

$$\pi_i(\varphi, \lambda_i^*(\varphi)) = \frac{R_i(\rho P_i \varphi \lambda_i^*(\varphi))^{\sigma-1}}{\sigma} - f_{pi} = 0, \tag{5}$$

where $\pi_i(\varphi, \lambda_i)$ denotes equilibrium profits from a variety of product i with consumer taste λ_i and firm productivity φ.

From equation (5), the higher a firm's productivity φ, the lower is the zero-profit cutoff for consumer tastes $\lambda_i^*(\varphi)$, and so the greater the probability of having a value for consumer tastes sufficiently high to profitably produce the product. With a continuum of products and independent distributions for consumer tastes, the law of large numbers implies that the fraction of products produced by a firm equals the sum of its probabilities of producing each product. Therefore, as the probability of producing each product is increasing in firm productivity, a key implication of the model is that a firm's product range is increasing in its productivity.

We now consider a firm's decision of whether to enter or exit. With a continuum of products and independent distributions for consumer tastes, a firm's expected profits across the continuum of products equals the sum of its expected profits from each product minus the fixed headquarters costs:

$$\pi(\varphi) = \int_0^1 \left[\int_{\lambda_i^*(\varphi)}^{\bar{\lambda}} \pi_i(\varphi, \lambda_i) \gamma_{zi}(\lambda_i)\, d\lambda_i \right] di - f_h, \tag{6}$$

where $\gamma_{zi}(\lambda_i)$ is the stationary distribution for consumer tastes, which, as discussed further in the Web Technical Appendix, is endogenously determined as a function of the entry and conditional distributions, $z_{ei}(\lambda_i)$ and $z_{ci}(\lambda_i)$, respectively.

Although consumer tastes for a firm's variety of a product are stochastic, the law of large numbers implies that all firms with the same productivity experience the same flow of total profits across the continuum of products in equation (6). Stochastic shocks to consumer tastes generate fluctuations in the profitability of individual products, which lead them to be added and dropped over time. However, these fluctuations in the profitability of individual products average out at the level of the firm, so that the evolution of total firm profits over time is determined solely by stochastic shocks to firm productivity.

[13] We follow Foster, Haltiwanger, and Syverson (2008) in differentiating between revenue- and quantity-based measures of productivity. As we show in the Web Technical Appendix, both measures are monotonically related to the firm productivity draw (φ) in the model. We note that a monotonic relationship between φ and revenue-based measures of productivity can also be achieved via a demand system with a variable elasticity of substitution, such as the quasi-linear preferences of Melitz and Gianmarco I. P. Ottaviano (2008). In that setting, equilibrium prices fall less than proportionately with productivity due to variable markups.

The value of a firm with productivity φ equals the flow of current profits plus the expected value of capital gains or losses as a result of a stochastic productivity shock, discounted by the probability of firm exit:

$$v(\varphi) = \begin{cases} \dfrac{\pi(\varphi) + \theta\left[\int_{\varphi^*}^{\overline{\varphi}} [v(\varphi') - v(\varphi)]\, g_c(\varphi' | \varphi)\, d\varphi'\right]}{\delta + \theta G_c(\varphi^* | \varphi)} & \text{for } \varphi \geq \varphi^* \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where the denominator on the right-hand side of equation (7) is the probability of firm exit, which equals the exogenous probability of firm death δ plus the endogenous probability of experiencing a productivity shock that induces exit $\theta G_c(\varphi^* | \varphi)$.

The presence of a continuum of products in the model implies that each firm draws a value for consumer tastes above the zero-profit cutoff $\lambda_i^*(\varphi)$ in a positive measure of products. For entry to be profitable, however, the value of the current profits across this positive measure of products plus the expected value of capital gains or losses must exceed the fixed headquarters costs. As total firm profits across the continuum of products $\pi(\varphi)$ are increasing in φ, and the probability of experiencing a productivity shock that induces exit $G_c(\varphi^* | \varphi)$ is decreasing in φ, the value of the firm in equation (7) is increasing in its productivity. Therefore, there is a zero-value cutoff productivity φ^* below which firms exit, which is defined by $v(\varphi^*) = 0$.

In an equilibrium with positive entry, the expected value of entry must equal the sunk entry cost, which requires the following free entry condition to hold:

$$V = [1 - G_e(\varphi^*)]\, \overline{v} = f_e, \qquad \overline{v} \equiv \int_{\varphi^*}^{\overline{\varphi}} v(\varphi) \left(\frac{g_e(\varphi)}{1 - G_e(\varphi^*)} \right) d\varphi, \tag{8}$$

where $[1 - G_e(\varphi^*)]$ is the ex ante probability of drawing a productivity above the zero-value cutoff φ^* upon entry, $g_e(\varphi)$ is the probability of drawing productivity φ upon entry, and $v(\varphi)$ is the solution to the Bellman equation (7).

General equilibrium is referenced by the following six variables and functions: the zero-value cutoff productivity below which firms exit φ^*, the zero-profit cutoff consumer taste for each product for a firm with the zero-value cutoff productivity $\lambda_i^*(\varphi^*)$, the endogenous stationary distribution for firm productivity $\gamma_g(\varphi)$, the endogenous stationary distribution for consumer tastes for each product $\gamma_{zi}(\lambda_i)$, the price index for each product P_i, and aggregate revenue for each product R_i. As shown in the Web Technical Appendix, these six variables and functions are determined by the following equilibrium conditions: consumer and producer optimization, goods and labor market clearing, free entry, the zero-profit cutoff condition for consumer tastes for each product, the equality of the mass of successful entrants and the mass of exiting firms, the equality of the outflow and inflow of firms from each value of consumer tastes, and finally the equality of the outflow and inflow of firms from each value of productivity.

The general equilibrium of the model features both steady-state product switching and steady-state firm entry and exit. Each period a measure of new firms incur the sunk entry cost, and those with productivity draws above the zero-value cutoff enter, while those with productivity draws below the zero-value cutoff exit. A surviving firm with unchanged productivity produces a constant range of products, but idiosyncratic shocks to consumer tastes for individual products induce surviving firms to drop a measure of the products previously produced and add an equal measure of products not previously produced. As stochastic shocks to a surviving firm's productivity occur, the range of products produced expands with an increase in productivity and contracts with a decrease in productivity. Firms exit endogenously when their productivity falls below the zero-value cutoff or exit exogenously when death occurs as a result of *force majeure* considerations.

As discussed further below, these and other features of the model are used to guide our empirical analysis. Before beginning that analysis, we describe our data.

II. Data Description

As part of its quinquennial Census of Manufactures (CMF), the US Census Bureau (hereafter "Census") collects information on the set of Standard Industrial Classification (SIC) categories produced by US manufacturing establishments (i.e., "plants"). This information is obtained from questionnaires plants are required to fill out by law under Title 13 of the United States Code. Each questionnaire has two parts. The first is common to all establishments and solicits general information about their operation, including their overall shipments (i.e., "output"), use of inputs (capital, production and nonproduction workers, and materials) and wagebills.[14] We use this information to examine differences between single- and multiple-product firms, and, along with industry price deflators provided by Eric J. Bartelsman, Randy A. Becker, and Wayne B. Gray (2000), to compute revenue-based measures of firms' labor and total factor productivity (TFP).[15] As noted in Section IC and discussed further in the Web Technical Appendix, both revenue- and quantity-based measures of productivity are monotonically related to the firm productivity draw (φ) in the model.[16]

The second part of each questionnaire varies depending on the industry in which the establishment operates. It lists the set of products that establishments in the industry typically produce, as well as a verbal description of each product.[17] Establishments are instructed to record their total shipments of each product.[18] In the event that an establishment also ships products not listed on the form, the questionnaire provides space for them to record any shipments in additional product codes. Establishments are assigned to industries according to information collected from previous censuses as well as other census surveys. Very large plants with substantial activity in a number of industries may receive more than one form. Very small plants, referred to as "administrative records," are not required to report output at the product level. These establishments represent a very small share of overall US manufacturing output and are typically ignored in US microdata research; we drop them here as well.

[14] CMF questionnaires define shipment value as goods' "net selling value f.o.b. plant to the customer after discounts and allowances," and excluding freight charges and excise taxes. Questionnaires used as part of the 1997 CMF are available at www.census.gov/epcd/www/econ97.html. All dollar-value data collected in the CMF are nominal.

[15] We measure firm TFP as the shipment-weighted average TFP of its plants. Plant TFP in a given census year is measured relative to other plants in its main industry in percentage terms using the multifactor superlative index number of Douglas W. Caves, Laurits R. Christensen, and W. Erwin Diewert (1982). This index accounts for plants' use of capital, production workers, nonproduction workers, and materials. Plant shipments, capital, and materials are deflated according to the four-digit SIC deflator of its major industry using deflators provided by Bartelsman et al. (2000). Wages are deflated by regional US consumer price indexes available at www.bls.gov. A plant's main industry is the four-digit SIC in which it has the largest value of shipments.

[16] We focus on revenue-based measures of productivity because data on physical units of output are not available for all products and because physical units of output are not comparable across firms for many products, e.g., cars. We note that Foster, Haltiwanger, and Syverson (2008) find a positive correlation between revenue- and quantity-based measures of productivity for a sample of 11 products for which it is possible to compute and compare both measures across firms.

[17] Questionnaires also collect information on establishments' "other" activities, such as "tasks performed for others using others' materials," which cannot be associated with a particular manufacturing product. We exclude these categories from our analysis.

[18] We note that the census does not collect information on firms' input use by product, and also that output deflators for five-digit SIC products are not available. As a result, measurement of establishments' use of inputs or revenue productivity within individual products is not possible.

We analyze product switching in the 1987 through 1997 censuses. We use a five-digit SIC category as our definition of a product and refer to two- and four-digit SIC categories as "sectors" and "industries," respectively.[19] As described in United States Department of Commerce (1989), manufacturing encompasses 20 sectors, 455 industries, and 1,440 products. As product-mix decisions are made at the level of the firm, we aggregate plants to firms to create a firm by product by census year dataset.[20] Using this dataset we track the products that firms add and drop across census years.[21] Given that a considerable body of research already examines firm creation and destruction, we focus on the features of product switching by surviving firms highlighted by our model. In particular, we neither treat exiting firms as those that drop all their products, nor entering firms as those that add all their products. For convenience, we often refer to firms that produce multiple products as "MP firms" and firms that produce a single product as "SP firms."

To provide a sense of the relative level of detail between sectors, industries, and products, consider "Nonferrous Wiredrawing and Insulating" (SIC 3357), which is one industry inside the "Primary Metal Industries" (SIC 33) sector. The 13 products in this industry range from copper wire (SIC 33571) to fiber optic cable (SIC 33579), and are listed in Table A1 of the Web Technical Appendix. Though these products share a grossly similar end use, they can differ substantially in terms of the materials and technologies required to manufacture them.

For the manufacturing sector as a whole, the typical two-digit sector has 24 four-digit industries and 76 five-digit products, as reported in Table A2 of the Web Technical Appendix. The number of products per sector ranges from a low of 12 in Leather (SIC 31) to a high of 178 in Industrial Machinery (SIC 35). Similarly, the average number of products per industry within sectors ranges from a low of 1.1 in Leather to a high of 5.1 in Printing and Publishing (SIC 27).[22] Nonferrous Wiredrawing and Insulating (SIC 3357), the industry highlighted above, is just one of 26 Primary Metal Industries, and its products represent 14 percent (13/90) of the total number of products in that sector. Products vary substantially in terms of how they are produced both within and across sectors, as shown in the last four columns of Table A2, which report the mean and standard deviation of products' 1997 capital and skill intensity by sector.[23]

We interpret the SIC categories used to record US manufacturing output as discrete partitions of the model's continuum of products, which become coarser as one increases the level of aggregation. With this interpretation, the model provides a natural explanation for the coexistence of single- and multiple-product firms. We think of firms producing a single product as those whose

[19] Output at the five-digit SIC level is the most disaggregate data available for all plants. While CMF questionnaires solicit information at the seven-digit SIC level, establishments also surveyed for other programs (e.g., Census Current Industry Reports) are permitted to report information at the five-digit level to alleviate their reporting burden.

[20] Firm identifiers are derived from firms' legal identities, and firms can consist of one or many establishments. Census uses an annual Company Organization Survey both to determine how new firms are organized and to keep track of changes in incumbent firms' ownership structure over time, e.g., the buying and selling of plants, the creation of new plants, or the closing of existing plants.

[21] SIC categories undergo minor revisions in each census year but experienced a major revision in 1987. Census uses an internally generated concordance to map product codes collected in censuses after 1972 to the 1987 revision. We focus on the 1987 to 1997 censuses because they are less sensitive to this concordance and exhibit high product-code consistency over time. To be conservative, we drop the roughly 1 percent of five-digit codes (representing roughly 5 percent of total value) that do not appear in all three censuses. We note that our findings are not sensitive to this procedure, and that we find (but do not report) similar results for other sample periods, e.g., the 1972 to 1982 censuses, where the concordance of collected and 1987-revision product codes is less precise.

[22] There is substantial variation in the precision of industry and product classifications. For example, Passenger Cars (SIC 37111) and Combat Vehicles (SIC 37114) are examples of products in the Motor Vehicle industry (SIC 3711), while Textbook Binding and Printing (SIC 27323) and Religious Books, Binding and Printing (SIC 27323) are examples of products in the Book Printing industry (SIC 2732).

[23] As the CMF does not collect information on input usage (or wages) by product, we measure a product's capital and skill intensity as the shipment-weighted average of all plants producing it.

Table 1—Prevalence of Firms Producing Multiple Products, Industries and Sectors in 1997

Type of firm	Percent of firms	Percent of output	Mean products, industries, or sectors per firm
Multiple product	39	87	3.5
Multiple-industry	28	81	2.8
Multiple-sector	10	66	2.3

Notes: The table categorizes firms according to whether they produce multiple products (five-digit SIC categories), industries (four-digit SIC categories), or sectors (two-digit SIC categories). Columns 1 and 2 summarize the distribution of firms and output, respectively. The final column reports the mean number of products, industries, and sectors across firms producing more than one of each.

range of products falls within a single five-digit category. MP firms, on the other hand, are those whose product range is wide enough to span several five-digit SIC categories.

Table 1 reports an average breakdown of SP and MP firms across the 1987 to 1997 census years in our sample, and also reports the average number of products, industries, and sectors MP firms produce. As indicated in the table, MP firms dominate: though they represent a minority of firms (39 percent), they account for a strong majority of shipments (87 percent). Multiple-industry and multiple-sector firms are similarly influential, responsible for 28 and 10 percent of firms but 81 and 66 percent of output, respectively. The final column of Table 1 reveals that the average MP firm produces 3.5 products, that the average multiple-industry firm manufactures in 2.8 industries, and that the average multiple-sector firm is present in 2.3 sectors.[24]

III. Empirical Evidence

Our model highlights a number of features of product switching that operate at the level of firms, products, and firm-products. We organize our empirical investigation of product switching in this section according to these levels of analysis. We note that the formal derivation of the model's implications is available in the Web Technical Appendix.

A. *Firm-Level Evidence*

In the model, firms with higher productivity produce a wider range of products than firms with lower productivity because their higher revenues per product allow them to cover the fixed costs of a larger measure of products. Idiosyncratic shocks to firm-product profitability drive steady-state adding and dropping of products within firms, while idiosyncratic shocks to firm productivity induce changes in the measure of goods firms produce.

The Relative Productivity of Multiple-Product Firms.—Table 2 compares the characteristics of single- and multiple-product firms in the 1997 census, though we note that results are similar in previous census years. The table reports the results of OLS regressions of the natural log of

[24] On average across the census years 1987 to 1997, the share of MP firms with a single plant is 84 percent compared to a share of 93 percent for all firms. Therefore, MP firms are more likely to operate several production facilities than SP firms, but multiple products are frequently produced within the same production facility.

Table 2—1997 Multiple-Product versus Single-Product Firm Characteristics

Firm characteristic	Multiple product	Multiple industry	Multiple sector
Output	0.66	0.67	0.92
Employment	0.58	0.61	0.86
Probability of export	0.12	0.12	0.16
Labor productivity	0.08	0.06	0.06
TFP	0.02	0.02	0.00

Notes: Results are from OLS regressions of log characteristics on a dummy variable indicating the firms' status as well as main industry fixed effects, i.e., the industry in which firms have the highest value of shipments. Regressions are restricted to the 110,414 observations for which all firm characteristics are available. All differences are statistically significant at the 1 percent level based on standard errors clustered by main industry except for multiple-sector firms' TFP.

the noted firm characteristic on a dummy variable equal to unity if the firm produces multiple products as well as main-industry fixed effects. As indicated in the table, MP firms are larger than SP firms in the same industry in terms of both shipments (0.66 log points) and employment (0.58 log points). We also find that MP firms have higher revenue-based labor and TFP than SP firms in the same industry.

Similar differences are found with respect to firms producing in multiple industries and in multiple sectors, except for the TFP differential between single- and multiple-sector firms. That difference is statistically indistinguishable from zero, perhaps due to the difficulties of measuring productivity in firms with disparate products that span two-digit sectors.[25] All remaining differences displayed in the table are statistically significant at the 1 percent level.

While our analysis is based on US census data, we note that other datasets are amenable to analyzing firms' product scope at various levels of aggregation. The publicly available Amadeus database published by Bureau Van Dijk, for example, contains information on EU firms' primary and secondary industries. We note that differences among single- and multiple-industry firms in those data are similar to the results reported in the second column of Table 2. Unfortunately, the manner in which Amadeus tracks changes in firms' industries over time makes it difficult to undertake comparisons of product-mix dynamics across US and EU firms.

Product Switching within Firms.—We examine product switching by dividing surviving firms into four exhaustive and mutually exclusive groups based on the manner in which they alter their mix of products between census years. Possible actions are: (i) *None*—the firm does not change its mix of products; (ii) *Drop*—the firm only drops products; (iii) *Add*—the firm only adds products; and (iv) *Both*—the firm both adds and drops products, i.e., "churns" products.

Table 3 reports firm activity across these dimensions for the pooled 1987 to 1997 censuses. Cells in panel A of the table report the average percent of firms reporting each activity across

[25] Our model implies that measurement of TFP for multiple-product firms is problematic if, as is the case here, data on inputs at the firm-product level are unavailable. See also Bernard, Redding, and Schott (2005) and Jan De Loecker (2008).

Table 3—Product Switching by US Manufacturing Firms, 1987 to 1997

Firm activity	All firms	Multi-product firms	Exporters	Large firms	Multi-plant firms
Panel A. Percent of firms					
None	46	20	38	39	25
Drop product(s) only	15	12	18	17	21
Add product(s) only	14	32	14	16	15
Both add and drop	25	36	31	28	38
Panel B. Output-weighted percent of firms					
None	11	6	6	10	5
Drop product(s) only	10	8	9	10	10
Add product(s) only	10	12	9	10	9
Both add and drop	68	75	76	70	77

Notes: Panel A displays average percent of surviving US manufacturing firms engaging in each type of product-changing activity across five-year intervals from 1987 to 1997. Panel B provides a similar breakdown but weighting each firm by its output. Products refer to five-digit SIC categories. The four firm activities are mutually exclusive. "Large firms" are defined as firms whose output is above the seventy-fifth percentile.

five-year census intervals, while cells in panel B report percentages weighted by firm output.[26] The five columns in each panel report results for all firms, MP firms, firms that export, firms whose shipments are above the seventy-fifth percentile ("large firms"), and firms with more than one manufacturing plant.

As indicated in panel A, an average of 54 percent of surviving firms alter their mix of products every five years, 15 percent by dropping at least one product, 14 percent by adding at least one product, and 25 percent by both adding and dropping at least one product. Comparing the results for all firms in the first column with those for MP firms in the second column, we find implicitly that SP firms are more likely to leave their product mix unchanged than MP firms. From the third column of the table, we find that exporters are more likely to change their product mix than nonexporters. Finally, from the remaining columns of the table, we see that large firms and multiple-plant firms also have above-average rates of product switching.[27]

The frequency and pervasiveness of product switching displayed in panel A of Table 3 is consistent with our model. In panel B of the table we report output-weighted results, which reveal that firms accounting for relatively large shares of output are more likely to add and drop products than smaller firms across columns. This behavior is also understandable in light of our theoretical framework, as more productive firms are more likely to have product ranges wide enough to span five-digit SIC categories, rendering them more likely to add and drop products. Since more productive firms in the model also produce more of each product and have larger

[26] Though the figures reported in the table correspond to the probabilities of product switching conditional on firm survival, it is straightforward to evaluate the unconditional probabilities of product switching for all firms by multiplying the figures in the table by the average probability of firm survival, which is roughly two-thirds.

[27] Results for SP firms, nonexporters, "small" firms, and single-plant firms are available upon request. An alternate decomposition of activity according to whether firms do not change their product mix, change their mix but do not net add or drop any products, change their product mix and net add products, or change their product mix and net drop products indicates that these actions on average occur 46, 12, 22, and 20 percent of the time, respectively, across census years.

TABLE 4—PRODUCT SWITCHING AND CHANGES IN FIRM CHARACTERISTICS, 1987 TO 1997

	Net drop	Net add	Observations	R^2
Log change in real output	−0.078***	0.096***	94,012	0.05
	(0.0093)	(0.0076)		
Log change in employment	−0.085***	0.078***	94,012	0.03
	(0.0100)	(0.0075)		
Log change in real output/worker	0.007**	0.018***	94,012	0.03
	(0.0038)	(0.0043)		
Change in TFP	−0.041***	0.031***	94,012	0.08
	(0.0070)	(0.0076)		

Notes: Table summarizes OLS regression results of log change in firm characteristics over five-year intervals according to whether firms net add or net drop products. Each row summarizes the regression for the noted dependent variable. Standard errors in parentheses are adjusted for clustering by product mix. Regressions include product mix by year fixed effects.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

total output, firms that switch products are likely to account for a larger share of output than of the number of firms. As indicated in the table, an average of 89 percent of all manufacturing output is produced by firms that change their mix of products across census years. Firms that both add and drop products account for the largest share of output, at 68 percent.

Product Switching and Firm Characteristics.—We examine the relationship between product switching and firm outcomes via OLS regressions of log changes in firm characteristics between census years on dummy variables capturing contemporaneous product-switching behavior,

$$\Delta Z_{jt} = \alpha_{mt} + \beta_1 NetDrop_{jt} + \beta_2 NetAdd_{jt} + \varepsilon_{jt}, \tag{9}$$

where ΔZ_{jt} represents the log difference in a firm outcome between census years $t-5$ and t; α_{mt} represents a full set of product mix by year fixed effects; *NetDrop* is a dummy variable that is equal to one if a firm reduces its net number of products and zero otherwise; and *NetAdd* is a dummy variable that is equal to one if a firm increases its net number of products and zero otherwise.[28] The firm characteristics we consider are real output, employment, and real revenue-based labor and TFP.[29] The regression results, reported in Table 4, include all surviving firms between the 1987–1992 and 1992–1997 censuses. The regression coefficients therefore capture the correlation between changes in the net number of products and changes in firm characteristics conditional on firm survival. Each row of the table reports results for a different firm-outcome

[28] The left out category encompasses firms that undertake no product switching or, if they do switch products, experience no net change in the number of products they produce. Similar results are obtained if an additional dummy variable is included for firms that engage in product switching but experience no net change in products. Though our regression focuses on net adding and dropping because these relate most closely to the predictions of the model, we note that an analogous specification using the Add, Drop and Both measures defined above also reveals statistically significant correlations between product switching and changes in measured firm characteristics.

[29] Results for nominal output and nominal output per worker are similar. Due to the unavailability of product-level price indexes, firms' product-level shipments are deflated by their corresponding industry-level deflators. The inclusion of product-mix-by-year fixed effects in the regression helps to alleviate concerns about product-year variation in prices.

regression. Standard errors adjusted for clustering by product mix are reported in parentheses below coefficients. The number of firm-year observations included in each regression, as well as each regression's R^2, are reported in the final two columns of the table.

As indicated in the table, we find that product switching is related to changes in firm characteristics in the way suggested by the model. We find that net product adding is associated with an increase in firm size (whether measured by output or employment) as well as revenue-based labor and TFP. Similarly, we find that net product dropping is associated with a decrease in firm size and TFP. Although the correlation between net product dropping and revenue-based labor productivity is positive rather than negative, the estimated coefficient is roughly an order of magnitude smaller than those for the other variables. As noted above, the structure of our model implies that measuring the productivity of multiple-product firms is problematic when data on inputs are unavailable at the firm-product level.

While the regression results in Table 4 establish that product switching is accompanied by changes in observed firm characteristics, we emphasize that they are correlations capturing an equilibrium relationship between endogenous variables. As product choice is endogenous, the regression coefficients capture both the nonrandom decision to change the net number of products and the impact of this decision on observed firm characteristics.

Potential Product-Category Mismeasurement.—Census devotes considerable resources to the accurate collection and verification of establishments' product-shipment data. As noted above, forms are designed to minimize measurement error by being tailored to the industry in which establishments operate, by listing the SIC categories (and descriptions) that establishments in the industry commonly produce, and by offering establishments space to record output in unlisted categories. After forms are collected, Census verifies the consistency of current responses with past responses and recontacts establishments whose data appear erroneous. Nevertheless, our analysis of product switching is susceptible to establishments' inaccurate transcription of SIC codes.

We believe our results to be robust to product-category mismeasurement for several reasons. First, we note that our use of five-digit SIC categories to define products requires only that firms correctly record the first five digits of the seven-digit SIC categories listed on the census questionnaire. Second, we find little evidence of spurious product switching in the data: less than 2 percent of firms across the 1987 to 1997 censuses, for example, are observed producing, not producing, and again producing the same product. Third, the results reported in Table 4 indicate correlations between product-switching behavior and separately recorded measures of firm characteristics such as size and input usage that are systematic and consistent with our model. The consistency of these and other empirical results with the predictions of the model is hard to square with simple explanations of mismeasurement based on classical measurement error.

Fourth, we note that we observe similar switching behavior with respect to even more easily identified four-digit SIC industries and two-digit SIC sectors. Table 5 compares firms' extensive-margin adjustments for products (column 1 reproduced from Table 3), industries (column 2), and sectors (column 3) using the same typology of activities as in Table 3. The first row of the table records the average share of firms making no adjustments between census years. Not surprisingly, product switching (54 percent) is more likely than industry switching (41 percent), and industry switching is more prevalent than sector switching (16 percent). Even so, product adding induces an average of 27 percent of firms to enter at least one new industry and 9 percent of firms to break into at least one new sector every five years. To the extent that adding industries and sectors requires adopting unfamiliar production and distribution technologies, these findings also suggest that firms' extensive-margin adjustments involve considerable changes in the nature and scope of firms.

Table 5—Sector and Industry Switching by US Manufacturing Firms, 1987 to 1997

	Percent of firms		
Firm activity	Product activity	Industry activity	Sector activity
None	46	59	84
Drop only	15	14	6
Add only	14	13	6
Both add and drop	25	14	3

Notes: Table displays average share of surviving firms that engage in product, industry, and sector switching across five-year intervals from 1987 to 1997. Product, industry, and sector activity refers to the adding and/or dropping of five-digit, four-digit, and two-digit SIC categories, respectively. The four firm activities are mutually exclusive.

As a final check, we examine how product switching varies depending on the main two-digit manufacturing sector of a firm. We find that the average percent of firms that alter their mix of products every five years varies from a low of 33 percent in Stone and Concrete (SIC 32) to a high of 71 percent in Printing and Publishing (SIC 27), as reported in Table A3 in the Web Technical Appendix. Product switching therefore appears to be a pervasive feature of the US manufacturing sector that is not driven by behavior in a few influential sectors.

B. *Product-Level Evidence*

In the model, there is a positive correlation between products' add and drop rates: while some firms not producing a product receive a positive demand shock and therefore add it, some of the incumbent producers receive a negative demand shock and hence drop it. Variation in product add and drop rates is governed by the probability of receiving a shock. "Turbulent" product markets, where idiosyncratic shocks are more likely, exhibit more frequent adding and dropping, other things equal, than "stable" products where shocks are less prevalent. A related feature of product switching at the product level concerns gross versus net changes in product output. As idiosyncratic shocks lead different sets of firms to add and drop the same product simultaneously, the model has gross changes in product output dominating net changes.

Product Add versus Drop Rates.—Figure 1 displays the mean rate at which five-digit SIC products are added and dropped by US manufacturing firms across the 1987 to 1997 censuses. A product's add rate in year t is computed as the number of firms adding the product between census years $t - 5$ and t divided by the average number of firms producing the product in both years. Drop rates are computed analogously. As shown in the figure, there is a clear positive correlation between the rates at which products are added and dropped. This correlation is statistically significant at conventional levels.[30]

The positive correlation between the rates at which US manufacturing products are added and dropped indicates that the extensive-margin adjustments we observe in the data cannot be explained solely in terms of a net reallocation of economic activity from one group of products to another. Such a net reallocation would imply a negative correlation between the rates of product adding and dropping, as growing products are frequently added and infrequently dropped, and declining products are frequently dropped and infrequently added. Although the fact that add

[30] Existing research on plant creation and destruction finds a positive correlation between plant entry and exit rates. See, for example, Dunne et al. (1989a) for the United States.

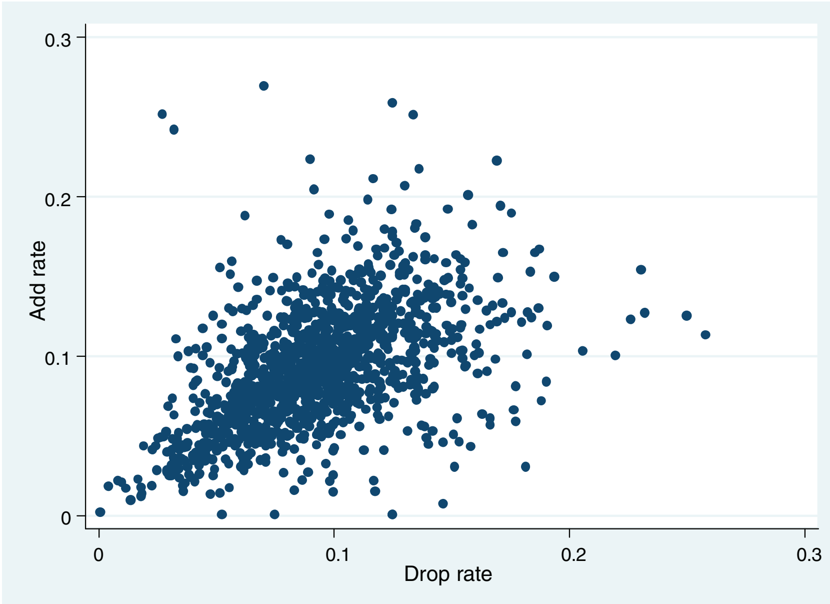

Figure 1. Average Product Add and Drop Rates, 1987 to 1997

Note: Add (drop) rates are defined as the number of firms adding (dropping) the product between census years divided by the average number of firms producing the product in both years.

and drop rates do not lie perfectly along a 45 degree line indicates that there is some net transfer of output across products in the data, other forces are also clearly at work.[31]

We note that while the positive correlation in Figure 1 is hard to reconcile with pure net reallocation *across* products, it does not rule out unobserved net reallocation *within* products. Indeed, in the model, net reallocation within products occurs because some firms add a product as other firms drop it.

Product Switching and Aggregate Output.—Our model points to product switching as a new dimension of resource reallocation that complements the more widely studied margin of plant or firm entry and exit. To assess the relative importance of this new dimension at the product and aggregate level, we decompose a product's output according to the type of firm producing it. In our first decomposition, we look backward in time to divide product output in year t according to firms that produce the product in both t and $t-5$ ("incumbents"), surviving firms that do not produce the product in $t-5$ but do produce it in t ("adders"), and firms that do not exist in $t-5$ but produce the product in t ("entering firms"),

$$Y_{tp} = \sum_{j \in B_{tp}} Y_{tpj} + \sum_{j \in A_{tp}} Y_{tpj} + \sum_{j \in N_{tp}} Y_{tpj}, \tag{10}$$

[31] In the model, a turbulent product with a high probability of idiosyncratic shocks to demand not only has high rates of product adding and product dropping but also displays a high volatility of shipments at firms that continue to produce it. Consistent with this implication, we find a positive correlation in the data between a product's rate of adding or dropping and its mean standard deviation of log shipments over time at firms that continue to produce the product.

where p indexes products; j denotes firms; and B_{tp}, A_{tp}, and N_{tp} represent the set of incumbents, adders, and entering firms, respectively.

Our second decomposition is forward-looking and divides a product's output in year t according to firms that produce the product in both t and $t + 5$ ("incumbents"), surviving firms that produce the product in t but not in $t + 5$ ("droppers"), and firms that produce the product in t but die between t and $t + 5$ ("exiting firms"),

$$(11) \qquad Y_{tp} = \sum_{j \in B_{tp}} Y_{tpj} + \sum_{j \in D_{tp}} Y_{tpj} + \sum_{j \in X_{tp}} Y_{tpj},$$

where D_{tp} and X_{tp} denote the sets of dropping and exiting firms, respectively.

The decompositions in equations (10) and (11) are attractive for our analysis for two reasons. First, because they are based on the nominal value of output in year t, they do not require product-level price deflators. Second, they can be converted into percentage decompositions for each product by dividing through by Y_{pt}. As a result, they do not require comparisons of output value across products and so avoid the problems associated with such comparisons.

Panel A of Table 6 reports the mean product-value decompositions in percentage terms across all products. Each row of the panel reports the average decomposition for a particular census year, with the first three columns looking backward (adding versus entering) and the final three columns looking forward (dropping versus exiting). In both cases we find that roughly two-thirds of the average product's output is produced by incumbents. The remaining output is more or less evenly split between firms adding or dropping the product and entering or exiting firms. In 1992, the only year of the sample for which both decompositions can be performed, adders and entrants are responsible for an average of 14 and 19 percent of products' output, respectively, while droppers and exiters account for 15 and 18 percent, respectively.

In panel B of Table 6, we report the results of a similar decomposition for the share of firms producing a product in a census year. While incumbents again make the greatest single contribution, their average share of firms, at 40 to 45 percent, is lower than their average share of output. Of the remaining 55 to 60 percent of producers, 29 to 37 percent are entering or exiting firms and 23 to 27 percent are adders or droppers. In Table A3 in the Web Technical Appendix, we report the results of these decompositions by two-digit sector. While there is some variation across sectors, we find substantial contributions of roughly equal magnitude from adders and droppers and entering and exiting firms in each two-digit manufacturing sector.

The breakdowns reported in Table 6 also highlight the fact that gross changes in product output are substantially larger than the associated net changes, an "excess reallocation" that is similar in spirit to the one found in job creation and destruction by Stephen J. Davis and Haltiwanger (1992). Indeed, comparison of the forward-looking 1992 decomposition with the backward-looking 1997 decomposition reveals that 15 percent of the average product's 1992 output is accounted for by firms that subsequently drop the product, while 15 percent of 1997 output is due to firms that just added it. Over the same period, the change in the average share of output represented by incumbents was just 3 percent (from 67 to 70 percent).[32]

[32] We find a similar dominance of gross versus net product switching in a decomposition of real US manufacturing growth that separates real output changes according to firm entry and exit, incumbents' product adding and dropping, and incumbents' continuing-product growth and decline. A disadvantage of that decomposition relative to the one presented here is its reliance on industry-level price indexes to deflate the output of all products within the same industry.

TABLE 6—DECOMPOSITION OF PRODUCT OUTPUT BY PRODUCER TYPE, 1987 TO 1997

	Average Share (percent) of product output in year t produced by:					
	Backward-looking			Forward-looking		
	Firms producing product in years $t-5$ and t (1)	Firms that add the product between years $t-5$ and t (2)	Firms born between years $t-5$ and t (3)	Firms producing product in years t and $t+5$ (4)	Firms that drop the product between years t and $t+5$ (5)	Firms that die between years t and $t+5$ (6)
Panel A						
1987	—	—	—	65	16	19
1992	67	14	19	67	15	18
1997	70	15	15	—	—	—
Panel B						
1987	—	—	—	44	27	29
1992	40	23	37	44	25	32
1997	45	26	29	—	—	—

Notes: The table reports average percentage decomposition of product output (panel A) and number of firms producing a product (panel B) according to firm activity. Columns 1–3 summarize backward-looking firm activities while columns 4–6 summarize forward-looking firm activities. Each row represents the average across all five-digit SIC products in the noted year. Decompositions cover the 1987 to 1997 censuses.

C. *Firm-Product Level Evidence*

In the model, a firm's profitability in a particular product is the result of an interaction between firm-wide productivity and consumers' taste for particular firm products. As a result, firms adding products are likely to have higher values of firm productivity than firms whose product range remains constant. Likewise, because consumer tastes are serially correlated and so are positively correlated with firm-product shipments and the length of time for which a firm has produced a product, firms are more likely to drop products that are small (scale dependence) or relatively new to the firm (age dependence). Finally, variation in consumer taste across products within firms results in differences in the size of shipments across products within firms.

Product Adding.—Firms' product-adding decisions are systematically related to their revenue-based productivity in existing products in the way suggested by the model. We find a positive association between initial firm revenue-based productivity and subsequent product adding among firms producing the same initial mix of products. Table 7 reports the results of OLS regressions of a dummy variable indicating product adding by either SP (columns 1–4) or MP firms (columns 5–8) between 1992 and 1997 on firm revenue-based productivity in 1992,

$$Add_{jt} = \alpha_m + \beta_1 Productivity_{jt} + \varepsilon_{jt}, \tag{12}$$

where α_m represents a set of product-mix fixed effects and $Productivity_{jt}$ is measured in terms of either revenue-based labor productivity or TFP. We employ a linear probability model so that product-mix fixed effects, which allow for a comparison of behavior among firms producing the same initial set of products, can be included in the regression. Given that we estimate the regression for a single cross section, the product-mix fixed effects control for the level and change of any product-mix-specific characteristic that influences the probability of adding a product between 1992 and 1997.[33]

[33] We find similar results for earlier census periods. The analogous specification when census periods are pooled involves including a full set of interactions between product mix fixed effects and time fixed effects. This specification also yields similar results.

Table 7—1992 to 1997 Product Adding OLS Regressions

	Single-product firms				Multiple-product firms			
	$\text{Add}_{t:t+5}$	$\text{Add}_{t:t+5}$	$\text{Add}_{t:t+5}$	$\text{Add}_{t:t+5}$	$\text{Add}_{t:t+5}$	$\text{Add}_{t:t+5}$	$\text{Add}_{t:t+5}$	$\text{Add}_{t:t+5}$
TFP_t	0.0140***	0.0150***			0.0020***	0.0026***		
	(0.0031)	(0.0031)			(0.0049)	(0.0049)		
$\ln(\text{output/worker})_t$			0.0099***	0.0114***			0.0178***	0.0137***
			(0.0023)	(0.0023)			(0.0044)	(0.0044)
$\ln(\text{employment})_t$		0.0269***		0.0271***		0.0268***		0.0265***
		(0.0012)		(0.0013)		(0.0022)		(0.0022)
$\ln(\text{age})_t$		0.0057***		0.0053***		0.0228***		0.0224***
		(0.0021)		(0.0021)		(0.0036)		(0.0036)
R^2	0.07	0.07	0.07	0.07	0.51	0.52	0.51	0.52
Observations	105,035	105,035	105,035	105,035	74,976	74,976	74,976	74,976

Notes: Table summarizes OLS regression results of a dummy variable indicating product adding by single-product (left panel) and multiple-product (right panel) firms between years t and $t + 5$ on year t covariates. Sample covers the five-year interval between 1992 and 1997. Regressions include product-mix and year fixed effects. Robust standard errors in parentheses are adjusted for clustering by product mix.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

As shown in the two panels of Table 7, subsequent product adding is positively and statistically significantly correlated with both initial TFP and initial revenue-based labor productivity for both SP and MP firms. As also shown in the table, this positive correlation remains when controls for firm size (i.e., employment) and age are included in the regression. These results are subject to the aforementioned caveats about the problems of measuring firm productivity when separate data on inputs are not available by product within firms. Nonetheless, they suggest that the revenue-based productivity advantage of MP firms observed in Table 2 is due at least in part to selection: SP firms that subsequently become MP firms have on average higher revenue-based productivity than other SP firms.[34]

Product Dropping.—We also find evidence of scale and age dependence in firms' decisions to drop products in line with the process of selection within firms emphasized by the model. Table 8 reports OLS regressions of a dummy indicating the dropping of one of a surviving firm's products between census years 1992 and 1997 on firms' 1992 relative product size ($Size_{jit}$) and relative product tenure ($Tenure_{jit}$), as well as both firm and product fixed effects:

$$Drop_{jpt} = \alpha_j + \alpha_p + \beta_1 \ln(Size_{jpt}) + \beta_2 \ln(Tenure_{jpt}) + \varepsilon_{jpt}, \tag{13}$$

where j and p index firms and products, respectively, and α_j and α_p represent firm and product fixed effects, respectively. The variables $Size_{jpt}$ and $Tenure_{jpt}$ are defined in terms of shipments and the length of time for which a firm has produced a product, respectively. Both size and tenure are measured relative to their averages for the product via log differencing in each census year. As a result, these variables control for differences across products in output and tenure, both at a point

[34] Our finding of a positive correlation between a firm's revenue-based productivity given its existing product mix and its decision to add a new product is hard to reconcile with a model in which products are randomly assigned to firms (see, for example, Roc Armenter and Mikos Koren 2008). Under random assignment, there would be no correlation between existing producer characteristics and the addition of a new product.

in time and over time. We note that we examine the model's firm-product predictions in the context of product dropping because construction of an analogous adding sample is impractical given the size of our dataset. Our sample consists of surviving firms, and therefore the estimated coefficients capture the determinants of a firm's decision whether to drop products conditional on firm survival.

As our regression specification is estimated for a single cross section of data based on the decision whether to drop a product between 1992 and 1997, the firm fixed effects control for any firm characteristic that is common across products and affects the decision whether to drop a product over this period (e.g., total firm shipments, the growth of total firm shipments, firm age, firm productivity, whether a firm is an exporter or enters/exits export markets, whether a firm has multiple plants). Similarly, the product fixed effects control for any product characteristic that is common across firms and influences the decision whether to drop a product (e.g., an aggregate change in relative demand or supply across products). The coefficients β_1 and β_2 are therefore identified solely from the variation in shipments and tenure that is idiosyncratic to individual pairs of firms and products.[35]

Results are reported with and without firm and firm-plus-product fixed effects. In all three cases, coefficient estimates indicate that firms are less likely to drop a product if their shipments and tenure are large relative to firms producing the same product.[36] To the extent that relative firm-product size and tenure are positively correlated with firm-product revenue-based productivity, the results in Table 8 suggest a systematic reallocation of economic resources within firms toward activities that generate more revenue per unit of factor input. As a result, studies of industry dynamics that ignore firms' extensive margins likely underestimate the role of reallocation in both output and revenue-based productivity growth.

Product Switching and Firm Output.—We find that the process of reallocation within firms captured in the model is quantitatively important at the firm level as well as at the aggregate level. To illustrate this, we decompose the output of surviving firms in a given census year according to whether the products are continuously produced versus recently added or about to be dropped. These backward- and forward-looking firm-level decompositions are analogous to those used for products in equations (10) and (11), respectively, above. Here, however, there is no contribution from firm entry or exit because the decompositions are undertaken for surviving firms.[37] As shown in Table 9, we find that on average 26 and 31 percent of firm output in 1992 and 1997, respectively, is represented by products firms added within the previous five years. A comparable average share of firm output, 29 and 26 percent for 1987 and 1992, respectively, is accounted for by about-to-be-dropped products. These shares suggest that product switching exerts considerable influence on firm activity, and that gross changes in firm output are substantially larger than net changes.

[35] We find similar results for earlier census periods. The analogous specification when census periods are pooled involves including a full set of interactions between firm and time fixed effects and between product and time fixed effects. This specification also yields similar results.

[36] In the model, consumer tastes follow a first-order Markov process, so that the probability of drawing a new value for consumer tastes depends only on the current value of consumer tastes. Furthermore, controlling for firm and product fixed effects, log firm-product shipments are proportional to the current value of consumer tastes. Therefore, as in much of the firm entry and exit literature, age or tenure should become insignificant in a specification that controls appropriately for scale. One natural explanation for the significance of firm-product tenure in such a specification is that consumer tastes follow a higher-order Markov process, and the model could be extended to allow for this possibility.

[37] We note that the product-level decompositions reported earlier are not simple averages of the firm-level decompositions reported here for additional reasons besides the focus on surviving firms. In particular, the weight of firms in the product-level decompositions varies substantially depending on their size, and the firm-level decompositions include a firm's output across all products.

Table 8—1992 to 1997 Firm-Product OLS Drop Regressions

	$\text{Drop}_{t:t+5}$	$\text{Drop}_{t:t+5}$	$\text{Drop}_{t:t+5}$
ln(relative product size)$_t$	−0.059***	−0.086***	−0.077***
	(0.001)	(0.001)	(0.001)
ln(relative product tenure)$_t$	−0.189***	−0.219***	−0.223***
	(0.006)	(0.008)	(0.008)
Fixed effects	None	Firm	Firm, product
R^2	0.48	0.48	0.47
Observations	80,371	80,371	80,371

Notes: Table summarizes OLS regression results of a dummy variable indicating a firm-product drop between 1992 and 1997 on 1992 firm-product attributes and fixed effects. Firm-product size and tenure are relative to their average values across firms for the product in a given year. The regression sample is surviving multiple-product firms. Robust standard errors in parentheses are adjusted for clustering by product.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 9—Average Decomposition of Firm Output by Type of Product, 1987 to 1997

	Average share (percent) of firm output in year t accounted for by:			
	Backward-looking		Forward-looking	
	Products produced in years $t-5$ and t	Products added between years $t-5$ and t	Products produced in years t and $t+5$	Products dropped between years t and $t+5$
1987	—	—	71	29
1992	74	26	74	26
1997	69	31	—	—

Notes: Table reports the average percentage decomposition of firm output according to whether products were previously (left panel) or subsequently (right panel) produced. Each row represents the average across all surviving firms in the noted year.

Distribution of Product Shipments within Firms.—To provide evidence on the product heterogeneity within firms featured in the model, Table 10 reports the average share of firm output represented by each of a firm's products, with products sorted from largest to smallest. To conform with census disclosure requirements, we report these average shares for firms producing up to ten products. We note that firms producing ten or fewer products represent roughly 99 percent of firms and roughly half of US manufacturing shipments in our sample. As shown in the table, the distribution of output across products is highly skewed, with the average share of firm output attributable to a firm's largest product declining from 80 percent for firms that produce two products to 46 percent for firms that produce 10 products.

A commonly used benchmark in the literature on firm size distributions is the Pareto distribution, which predicts a log linear regression relationship between the log rank of firm shipments and log firm shipments. To similarly assess the product-size distribution within firms producing a like number of products, we estimate an analogous regression of the log rank of firm-product

Table 10—Mean Distribution of Within-Firm Output Shares, 1987 to 1997

		Number of products produced by the firm									
		1	2	3	4	5	6	7	8	9	10
Average percent of output	1	100	80	70	63	58	54	52	50	48	46
	2		19	21	22	21	21	21	20	20	20
	3			7	9	10	11	11	11	11	12
	4				4	5	6	7	7	7	7
	5					2	3	4	4	5	5
	6						2	2	3	3	3
	7							1	2	2	2
	8								1	1	2
	9									1	1
	10										1

Notes: Columns indicate the number of products produced by the firm. Rows indicate the share of the products in firm output, in descending order of size. Each cell is the average across the relevant set of firm-products in the sample. Sample includes all firms producing at least ten products in the 1987 to 1997 censuses.

size on the log of their share of firm shipments.[38] We estimate this regression separately for firms producing four, six, eight, and ten products using the data on the average shares of products in firm output reported in Table 10. The fitted and actual values for firm-product rank and size in these regressions are displayed in Figure 2. As indicated in the figure, actual values lie above the regression line in the middle of the distribution and below the regression line in the tails, implying thinner tails than the Pareto distribution.[39] Therefore, the heterogeneity across products within firms stressed in our model displays the same features as the heterogeneity across firms examined in the firm-size distribution literature (see, for example, Rossi-Hansberg and Wright 2007).

D. *Alternate Explanations*

Our empirical analysis of product adding and dropping thus far accords well with features of product switching highlighted by our model of endogenous product selection. Here, we discuss potential alternate explanations for the facts we uncover and the extent to which they receive support from the data.

Explanations of product switching fall into three broad categories according to whether they focus on factors that are specific to products, on factors that are specific to firms, or on factors that are idiosyncratic to firm-product pairings. The first category of explanations emphasizes forces that are product specific but common to all firms, such as changes in relative demand (e.g., changing fashions) or relative supply (e.g., changing technology). Explanations of this form that involve a net reallocation of economic activity across products, e.g., from "cold" to "hot" products, are hard to reconcile with the positive correlation between products' add and drop rates observed in Figure 1.

[38] If the distribution of shipments, x, across products within firms shown in Table 10 is Pareto with minimum value k and shape parameter a, we have $\Pr(x > x') = (k/x')^a$. Taking logarithms in this expression and rearranging terms yields the following relationships: $\log(Rank_p) = A - a\log(x_p) = B - a\log(Share_p)$, where $Rank_p$ is the rank of x_p, $Share_p = x_p/X$, and A, B, and $X = \sum_p x_p$ are constants.

[39] Including a quadratic term in log product size in the regression, we find that a null hypothesis of linearity is strongly rejected at conventional levels of statistical significance. From a comparison of the tails across the panels of Figure 2, the departures from a Pareto distribution increase with the number of products that firms produce.

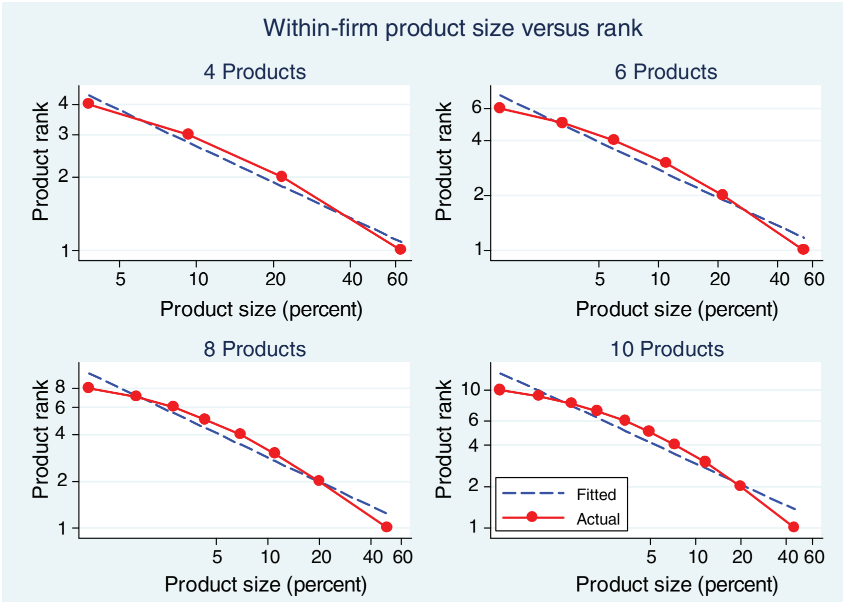

Figure 2. Distribution of Product Shipments within Firms, 1987 to 1997

Notes: The solid line plots within-firm product rank against within-firm product size. Dashed lines are the result of an OLS regression of log product rank on log product size.

A second class of explanations for product switching focuses on factors that are specific to firms but common to products. Positive shocks to a firm's productivity, for example, might increase the profitability of all products it could produce, thereby inducing the firm to add previously unprofitable products. This class of explanations, however, is hard to reconcile with the fact that firms simultaneously add and drop products across census years. Such switching suggests that any firm-specific shocks differentially affect its products, and are therefore firm-product specific. A more fundamental challenge for both firm- and product-specific explanations of product switching is our finding that firm-product characteristics are influential determinants of product switching, even after controlling separately for firm and product characteristics.

The model developed in Section I falls into the third category of explanations, which concentrates on the role of firm-product attributes in influencing product switching. In our model, the interaction of idiosyncratic shocks to firm productivity and firm-product demand fosters both self-selection of firms and self-selection of products within firms. Klette and Kortum (2004)—hereafter KK—offer an alternate firm-product approach that emphasizes innovation.[40] In the KK model, products cycle across firms as they exchange technological dominance. While this model is consistent with some of the stylized facts we present (e.g., product switching across census years), it fails to capture others. In KK, for example, the firm-size distribution is determined entirely by variation in the extensive margin of the number of products firms produce. In the data, however, we find that the intensive margin of output per product is quite influential in determining variation in firm size.[41]

[40] See also Rasmus Lentz and Dale T. Mortenson (2005), Luttmer (2008), and Chatterjee and Rossi-Hansberg (2008) for other innovation-based models of firm scope.

[41] Regressing the log of firm average output per product (the intensive margin) and the log of firm number of products (the extensive margin) on the log of firm total output, we find that the intensive margin accounts for around 90 percent of the cross-section variation in firm size.

The KK model also predicts a constant hazard rate—equal to the economy-wide rate of creative destruction—for firms' dropping of products. Here, however, we find that the probability that a firm drops a product is decreasing in firm-product shipments and the length of time for which the firm has produced the product. Though our data motivate the development of the selection model described above, we believe that extending innovation-based models to match our new stylized facts is another interesting avenue for further research.

IV. Extending the Basic Selection Model

In this section we highlight several dimensions of the data that are less well captured by either our model or the alternative potential explanations discussed above, but which point to potentially fruitful lines of future theoretical and empirical research.

A. *Product Coproduction*

Our first set of additional results relates to the types of goods firms tend to produce together. Table 11 reports the average annual frequency, in thousands, with which firms coproduce products within and across sectors from 1987 to 1997. Dark shading indicates coproduction that is significantly more frequent than expected based on the individual probabilities of producing each product, while light shading indicates significantly less coproduction.[42] As shown in the table, the probability that a firm produces a product in the row sector conditional on production of a product in the column sector is relatively high within sectors as well as between sectors that appear related (e.g., Apparel and Textiles, or Electronics and Industrial Machinery). Furthermore, the matrix of data as a whole rejects the null hypothesis that the probability a firm produces a product is independent of the firm's other products (p-value < 0.01).

In developing our model, we assumed for simplicity that consumer tastes λ_i were independently distributed across products. As a result, the only interdependence in firm sales across products arises from firm productivity φ, which raises or reduces a firm's sales across all products proportionately. However, the findings in Table 11 suggest richer forms of interdependence, where some pairs of products are systematically coproduced within firms, while other pairs of products are systematically produced in separate firms.[43] One way of extending the model to capture richer forms of interdependence is to allow consumer tastes (or equivalently a product-specific component of productivity) to be correlated across products. For example, product characteristics that are highly valued in one product market (e.g., apparel) may be highly valued in another product market (e.g., textiles). While such an extension would bring the model closer to the data, this would come at the cost of making the model considerably less tractable. Nevertheless, achieving greater understanding of the sources of interdependence in demand or production technology across products within firms would be useful.

[42] We assess statistical significance by comparing the observed coproduction frequencies to those that would be expected under a null hypothesis that the decisions to produce row and column product lines are independent. Under this null, the expected frequency with which a particular pair of major sectors is coproduced follows an independent Poisson distribution. An individual cell's deviation from random coproduction therefore follows a standard normal distribution, $((o_{rc} - e_{rc})/\sqrt{e_{rc}}) \sim N(0,1)$, where o_{rc} and e_{rc} are the observed and expected frequencies in row r and column c, respectively. Summing across cells, the statistic for testing whether the entire matrix of frequencies is generated by random coproduction, $\sum_{r,c} (o_{rc} - e_{rc})^2/e_{rc}$, is distributed chi-squared.

[43] Similarly, the coproduction findings in Table 11 sit awkwardly with the assumption in the innovation-based model of Klette and Kortum (2004) that the identity of the product to which a firm's innovation applies is drawn randomly from the set of potential products.

Table 11—Product Coproduction within Firms, 1987 to 1997

Sector	20	31	30	22	23	39	24	26	25	27	28	29	32	33	34	35	36	37	38
20 Food	158	2	9	5	16	5	6	9	6	11	42	3	4	6	15	16	8	5	4
31 Leather	2	1	1	1	3	1	1	1	1	1	1	0	0	1	2	1	1	0	0
30 Rubber and plastic	9	1	47	8	9	7	8	10	6	6	24	2	6	13	33	41	22	12	11
22 Textile	5	1	8	25	18	3	3	4	3	4	11	1	2	4	8	8	5	3	3
23 Apparel	16	3	9	18	64	6	6	6	6	9	12	1	3	7	20	21	9	5	5
39 Miscellaneous	5	1	7	3	6	10	3	3	2	9	6	0	1	3	10	9	6	3	3
24 Lumber	6	1	8	3	6	3	79	16	16	5	9	1	4	5	16	10	6	3	3
26 Paper	9	1	10	4	6	3	16	19	3	23	13	1	3	5	12	12	6	2	4
25 Furniture	6	1	6	3	6	2	16	3	23	3	4	0	1	4	12	10	7	3	3
27 Printing and pub.	11	1	6	4	9	9	5	23	3	401	10	1	2	5	13	15	10	4	5
28 Chemicals	42	1	24	11	12	6	9	13	4	10	74	13	10	16	25	29	20	10	18
29 Petroleum	3	0	2	1	1	0	1	1	0	1	13	4	2	3	4	3	2	1	1
32 Stone and concrete	4	0	6	2	3	1	4	3	1	2	10	2	10	6	11	11	7	3	3
33 Primary metal	6	1	13	4	7	3	5	5	4	5	16	3	6	27	48	47	29	15	10
34 Fabricated metal	15	2	33	8	20	10	16	12	12	13	25	4	11	48	124	117	53	30	22
35 Industrial mach	16	1	41	8	21	9	10	12	10	15	29	3	11	47	117	119	72	38	31
36 Electronic	8	1	22	5	9	6	6	6	7	10	20	2	7	29	53	72	70	25	37
37 Transportation	5	0	12	3	5	3	3	2	3	4	10	1	3	15	30	38	25	18	10
38 Instruments	4	0	11	3	5	3	3	4	3	5	18	1	3	10	22	31	37	10	14

Notes: The table summarizes coproduction of five-digit SIC categories across multiple-product firms. Cells report count (in 000s) of the average number of firms producing two products in the noted sectors across 1987 to 1997. Dark (light) shading indicates coproduction that is statistically significantly higher (lower) at the 1 percent significance level than is implied by a null hypothesis of random coproduction (see text). Sectors have been sorted to maximize dark shading along the diagonal (see text).

B. *Modes of Product Switching*

Our second set of additional results relates to the mode by which firms add and drop products. There are a variety of ways in which firms can add a product: at existing facilities, at newly constructed plants, or by acquiring an existing plant from another firm. Similarly, firms can drop products at continuing plants by closing plants or by selling plants to another firm.

Table 12 reports the distribution of product adds (panel A) and drops (panel B) according to how they are accomplished. As indicated in the first column of each panel, roughly 85 percent of added and dropped products, respectively, are added and dropped at existing plants. The share of the number of products added and dropped through mergers and acquisitions (M&A) is relatively

Table 12—How Products are Added and Dropped, 1987 to 1997

	Share of products		Share of firms	
	Unweighted	Value-weighted	Unweighted	Value-weighted
Panel A. Method of product adding				
Existing plant(s) only	0.862	0.412	0.899	0.259
Acquired plant(s) only	0.055	0.259	0.013	0.048
New plant(s) only	0.060	0.120	0.030	0.044
Combination with M&A	0.013	0.147	0.031	0.488
Combination without M&A	0.011	0.061	0.027	0.161
Panel B. Method of product dropping				
Existing plant(s) only	0.835	0.320	0.898	0.213
Divested plant(s) only	0.052	0.282	0.007	0.018
Closed plants only	0.084	0.123	0.037	0.042
Combination with M&A	0.015	0.231	0.026	0.538
Combination without M&A	0.013	0.045	0.033	0.189

Notes: Table reports the manner in which firms add (panel A) and drop (panel B) five-digit SIC products. The first two columns report the distribution with respect to products; the second two columns report the distribution with respect to firms. Figures shown are averages across the pooled 1987 to 1997 sample.

small: less than 10 percent of both adds and drops involve plant acquisitions or divestitures whether by themselves or in combination with another mode of product switching. However, as shown in the second column of each panel, M&A activity is substantially more important as a share of the value of products added and dropped, indicating that the products added and dropped through plant acquisitions or divestitures are on average larger than those added and dropped through other modes of product switching. The third and fourth columns of each panel show that a similar pattern is observed for the share of firms that add and drop products.

A distinct but related issue is the extent to which M&A is accompanied by any of the modes of products switching. Comparing product and sector switching according to whether firms concomitantly acquire or divest a plant, we find that firms involved in an ownership change are relatively more likely to change their mix of products, as reported in Table A4 in the Web Technical Appendix. An average of 94 percent of firms that engage in M&A activity also alter their mix of products, compared with an average of 53 percent for firms that do not participate in an acquisition or divestiture. For sector switching, the importance of M&A is even more stark: the analogous percentages are 67 and 15 percent.

While our finding that product switching frequently occurs within firms' existing plants motivates the model's abstraction from M&A and the creation of new plants, the introduction of these complementary modes of product switching is an interesting area for further research.

V. Conclusions

The extent to which resources are allocated to their best use is a primary concern of economics. Virtually all empirical research on reallocation as a source of industry output and measured productivity growth focuses on plant or firm entry and exit or changes in the composition of output across plants or firms. This paper identifies product switching as an important source of reallocation within firms and analyzes its determinants and consequences.

Guided by a natural extension of existing models of industry dynamics that allows firms to produce an endogenous range of products in response to evolving firm and product characteristics, we develop a body of evidence about this new dimension of firm behavior. Using a novel dataset that tracks US manufacturing output at the level of five-digit products within firms, we find that firms add and drop products with surprising intensity and frequency. On average, 54 percent of US manufacturing firms alter their mix of five-digit products every five years, and these adjustments lead an average of 41 percent of firms to enter new or exit existing four-digit industries, and 16 percent of firms to extend or contract their set of two-digit sectors. Overall, we find that the gross contributions of product adding and dropping to the evolution of aggregate manufacturing output are as large as the gross contributions of firm entry and exit.

We demonstrate that observed patterns of product switching are inconsistent with explanations based purely on net reallocation across products, and are more generally hard to reconcile with explanations based on firm or product shocks alone. In contrast, we find support for the central features of our extended model of industry dynamics, which emphasizes selection within as well as across firms. In particular, the model accounts for the positive correlation across products between the rate of product adding and dropping and the age and scale dependence observed in the probability a product is dropped.

Though our basic framework is a good match for key features of the census data, additional empirical analysis reveals areas in which it might be extended. In the current version of the model, for example, the only source of dependence in profitability across a firm's products is the firm's overall productivity: higher firm productivity raises the profitability of all products. Empirical examination of firms' product mix, however, reveals that firms are more likely to co-manufacture products within the same industry, or within "linked" industries, e.g., lumber and furniture or electronics and instruments. An extended version of our model might incorporate demand- or supply-side complementarities that rationalize these links. Similarly, extending the model to allow firms to endogenously choose between various modes of product switching, such as plant creation and M&A, is another interesting avenue for future research.

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