SWIMMING UPSTREAM: INPUT-OUTPUT LINKAGES AND THE DIRECTION OF PRODUCT ADOPTION

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Abstract. Multiproduct firms dominate production, and their product turnover contributes substantially to aggregate growth. Firms continually adapt their product mix, but what determines which products firms expand into? Theories of the firm propose that mulitproduct firms choose to make products which need the same know-how or inputs that can't be bought 'off the shelf'. We empirically examine this rationale by testing for firm-level capabilities that are shared across products and manifested through input-output (IO) linkages. We show that a firm's idiosyncratic horizontal and vertical similarity to a product's IO structure predicts product adoption. Using product-specific policy changes for a firm's inputs and outputs, we show that input linkages are the most important, suggesting that firms' product capabilities depend more on economies of scope rather than product market complementarities.

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Keywords: Multiproduct firms, product adoption, vertical linkages, horizontal linkages.

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1. Introduction

Multiproduct firms dominate production and export activity, and their continual product turnover contributes substantially to aggregate output growth. In the United States, multiproduct firms account for over 90 per cent of manufacturing output and multiproduct exporters account for over 95 per cent of exports. About 89 per cent of multi-product firms vary their product mix within five years and these changes in the product mix make up a third of the increase in US manufacturing output (Bernard et al. 2007, 2010a). Firms continually adapt their product mix, and expanding along a few core products is an important channel through which firms adjust to changes in their economic environment (Bernard et al. 2010a, 2011; Eckel and Neary 2010; Mayer et al. 2009; Iacovone and Javorcik 2010). But what determines *which* products firms adopt?

Recent work emphasizes the importance of core products, but less is known about what constitutes the core competencies of firms. Theories of the firm, dating back to Penrose (1955), take the view that a firm consists of a bundle of productive capabilities that can be used to produce a variety of products. Firms grow by diversifying into new products, and by therefore avoiding the limits to growth imposed by the size of a single product market. Successful product diversification is the main engine of corporate growth that enables firms to grow faster than the markets they operate in (Marris 1964). Teece (1982) draws on this insight to provide a rationale for multi-product firms. Firms are able to diversify because their productive capabilities "lie upstream from the end product," as experienced during wartime when auto manufacturers quickly switched to making tanks, chemical companies to making explosives, and radio manufacturers to making radar. Firms choose to be multiproduct, rather than operate as separate single-product firms, when the productive capabilities of the firm can be shared across products without complete congestion, leading to economies of scope. However, just like an upstream input producer and a downstream producer need not be vertically integrated, two products that have economies of scope need not be produced within the same multiproduct firm. A multiproduct firm emerges when production of different products regularly requires the same know-how or inputs, that can't be bought 'off the shelf' (Teece 1980; Sutton 2012). We empirically examine this rationale for multiproduct firms by testing for *firm-level* capabilities that are shared across products.

Firm-level capability is typically modeled as an idiosyncratic firm-level "productivity" shifter, that leads to differences in firm-level decisions and outcomes (Melitz 2003).

We generalize a firm's idiosyncratic productivity to a high dimensional firm-input and firm-output vector. Although input-output capabilities are not the ultimate sources of differences across firms, they are performance-relevant outcomes of the firm's underlying capabilities that can be directly measured with firm-level surveys. We examine both horizontal and vertical firm-level IO complementarities in diversification. The horizontal firm-industry IO measures determine the extent to which firms move into industries that have a similar IO mix. For instance, a car producer with a superior capability to mold steel into vehicle components is more likely to move into bus production than candy manufacturing. Our measures of horizontal linkages are related to Conley and Dupor (2003) who show that IO relations characterize interactions between sectors. Taking their sectoral analogy to the firm-industry level, we define a firm to be horizontally similar in inputs to an industry if the firm buys inputs in similar proportions to the average input shares in that industry. Similarly, a firm is horizontally similar in outputs to an industry if the firm's sales of all its outputs is in similar proportions to the average output shares of firms in that industry.[1]

The vertical measures examine whether firms move into industries that are upstream to its outputs or downstream to its inputs. For instance, a firm selling a higher share of cotton garments could be more likely to move into cotton yarn production, rather than wool production. We define a firm as having stronger upstream linkages to an industry if the firm has a higher expected input share from that industry given the firm's observed output shares. Similarly, a firm has stronger downstream linkages to an industry if the firm has a higher expected output share in that industry, given the firm's observed input shares. The upstream and downstream measures capture the linkages that are commonly emphasized in the vertical integration literature (e.g. Antras and Chor 2013).

Using detailed firm-level IO data and a product-level IO matrix, we construct 262 measures of horizontal and vertical IO linkages per firm and test for firm-level IO capabilities. Controlling for firm and product effects in each period, we find that firms are more likely to move into products which have horizontal and vertical linkages to its existing IO mix. The estimated magnitudes of these effects are large relative to average product adoption rates. These effects remain after controlling for all product adoption rates for each main firm product each period, showing that idiosyncratic firm-level

[1]We focus on output sales shares of firms (rather than expenditure shares of buyers) because we are interested in the extent to which firms can internalize the linkages across their products by bundling their sales and not in the pure demand complementarities that might accrue to buyers but cannot be internalized by firms.

input linkages drive product adoption. Horizontal and vertical *input* linkages dominate *output* linkages in predicting product adoption.[2] The differences in these effects are more stark when considering the impact of product dereservation which isolates each linkage mechanism.

Our findings provide microeconomic evidence for the ideas of product space developed by Hausmann and Hidalgo (2011), and Hausmann et al. (2007) and Sutton and Trefler (Forthcoming) at the country level. They propose that products differ in the capabilities needed to make them and countries differ in the capabilities they have. Countries make products for which they have the requisite capabilities, and they tend to move to goods close to those they are currently specialized in (Hidalgo et al. 2007). Product specialization patterns of countries however are not uniquely determined by fundamentals such as factor endowments, as proposed by new trade theory models (Helpman and Krugman 1985). Idiosyncratic elements contribute towards determining which countries make which goods, and the distributions of the country-capability and product-capability matrices have some degree of randomness. The resulting product specialization patterns matter for differences in economic growth across countries, because countries located in more connected parts of the product space are able to grow faster. While these papers look at the product space at the macroeconomic level, we provide proximate evidence for the influence of firm-level capabilities on the direction of product adoption. The findings support a fundamental assumption of these theories: firms have an incentive to internalize interlinkages across products. This concretizes the proposal of Hausmann and Hidalgo (2011) that the cost of developing a regional jet aircraft is likely to be lower for a firm that has previously developed a transcontinental aircraft and a combustion engine, relative to a firm that has previously produced only raw cocoa and coffee. Our findings also empirically address the questions raised by Wernerfelt (1984): on which of the firm's resources are diversification based, and into which products will diversification take place?

We identify horizontal and vertical linkages across products in their use of inputs, which include material inputs and capital goods. This gives support to the theory of diversification based on vertical economies and horizontal economies, which says that firms would diversify into upstream inputs and products which use common inputs.[3] Our findings do not imply that diversification motivated by other factors, such as

[2]Lu et al. (2016) demonstrate the inherently dynamic process of accumulating input capabilities and it's role in increasing firm productivity.

[3]This is distinct from diversification based on financial economies, where firms diversify into unrelated products to hedge their risks by pooling together products with imperfectly correlated income streams (Hill and Hoskisson 1987).

financial economies or economies of scope in other inputs such as labor, do not exist. In our most stringent specification, we exploit variation from changes in industrial policy that affected inputs and outputs differentially. As these policy changes are arguably uncorrelated with the other sources of interlinkages, we can determine the contribution of firm-level input linkages across products without ruling out these other sources of diversification.

Interlinkages across products are a potentially important channel for aggregate productivity growth in the development process, which has motivated policies such as domestic content requirements that continue to prevail across the developing world (Harrison and Rodriguez-Clare 2009). While we do not look at product linkages across firms, our results for within-firm product linkages demonstrate the existence of cross-product spillovers. These have been difficult to identify across firms due to confounding factors, such as unobserved demand shocks, that are correlated with outcomes of interest like productivity and product innovation. Looking within firms lets us control for many of these confounding factors and to get a causal interpretation of shared input capabilities on product adoption by focusing on variation driven by policy changes. The industrial policy we exploit eased entry barriers in previously reserved industries and has been of interest in understanding competition, employment generation and misallocations in manufacturing (Martin et al. 2014; Garc'ia-Santana and Pijoan-Mas 2014; Galle 2015). Certain industries were previously reserved for production only by small scale firms, and over time large firms were allowed to compete with small scale firms in these industries. As the reservation policy restricted sales by large firms in the reserved industries, it is striking that we find that dismantling the policy affected large firms primarily through the channel of better access to inputs, rather than through complementarities in dereserved output markets. This is consistent with Goldberg et al. (2009) who find that publicly listed firms in Indian manufacturing increase their range of products in response to input tariff liberalization. Vandenbussche and Viegelahn (2014) also show that Indian firms move away from inputs facing domestic anti-dumping measures by decreasing sales of products using these inputs. Koren and Tenreyro (2013) explain the macroeconomic significance of this vertical input linkage channel by showing that the concentrated use of inputs by firms in developing countries can be a source of low aggregate productivity and high volatility in growth rates. This implies that the reservation policy could also have consequences for increased volatility due to constraints on the product diversification for large firms. We find that the input channel operates directly through vertical upstream linkages and indirectly through horizontal input similarity, suggesting that industrial policies produce cascading effects in sectors that are not directly linked to the industry.

A growing macro literature stresses the importance of input linkages in amplifying micro shocks and policy effects. Acemoglu et al. (2012) show that the US economy has a small number of sectors that play a disproportionate role as input suppliers to others. Consequently, idiosyncratic distortions in such sectors get amplified into large aggregate productivity differences and generate aggregate fluctuations by propagating micro-level shocks. In a similar vein, Carvalho (2008) shows that input linkages drive co-movement across sectors. The intuition is that a shock to the production technology of a general purpose sector, such as petroleum refineries, propagates to the rest of the economy. Changes in the productivity of a narrowly defined but broadly used input therefore translate into cyclical aggregate fluctuations.

Going beyond these direct upstream linkages, higher-order interconnections across sectors imply that low productivity in one sector leads to a reduction in production of a sequence of sectors interconnected to one another, creating cascade effects. The horizontal IO linkages we consider capture these cascade effects. While we look at the firm-industry level, our horizontal linkage measures are similar to the sector-level horizontal linkage metrics of Conley and Dupor (2003), who show that covariance in productivity growth across sectors is a function of the horizontal IO distances between sectors. They find that cross-sector productivity covariance tends to be greatest between sectors which are similar in inputs, and that the positive cross-sector covariance of productivity growth generates a substantial fraction of the variance in aggregate productivity. Looking at firm-specific shocks, di Giovanni et al. (2014) show that IO linkages are the key mechanism through which microeconomic shocks propagate and lead to aggregate fluctuations in France. Earlier work by Jovanovic (1987) and Durlauf (1993) also emphasized strong strategic complementarities across firms and showed that such complementarities may translate firm level shocks into volatility at the aggregate level.

At the micro level, the business literature documents that firms tend to diversify into products that have IO linkages with each other, suggesting technological and demand complementarities across products.[4] Building on this literature, we test for the contribution of firm-level IO capabilities as a source of product diversification within firms. Our findings are related to Aw and Lee (2009) who focus on four Taiwanese electronics industries and estimate cost functions to arrive at the incremental marginal cost of the

[4]E.g. Scherer 1982; Robins and Wiersema 1995; Bowen and Wiersema 2005; Bryce and Winter 2009; Fan and Lang 2000b; Schoar 2002; Liu 2010; Rondi and Vannoni 2005 for developed countries.

core product when the firm adds a new product. This provides a cost-based measure of supply linkages across products, and they find that firms move towards specializing in core products. After controlling for plant characteristics, multi-product plants tend to drop products that are dissimilar to their core products. While Aw and Lee focus on one sector, we study supply linkages for all manufacturing industries and show that supply linkages are important across several manufacturing products. A growing number of studies relate linkages to productivity (see the forthcoming handbook chapter by Combes and Gobillon (2014)). In particular, Lopez and Sudekum (2009) find that upstream, but not downstream, linkages are associated with higher productivity, perhaps in part due to the stronger effect of upstream linkages on product adoption that we find. In innovative work, Flagge and Chaurey (2014) use a moment inequality methodology to estimate bounds on the costs of adding products, including the role of product proximity measures.

The remainder of the paper proceeds to describe Indian multi-product firm data and the basic patterns and dynamics of products produced as well as the impact of product dereservation on firm level expenditures and sales. Section 4 estimates the role of horizontal and vertical linkages in product adoption and Section 5 concludes.

2. Indian Manufacturing Firm Data and the Impact of Dereservation

This section describes the Indian manufacturing data used and the impact of product dereservation on firm expenditures and sales. Appendix 2.3 describes the nature of product turnover in multiproduct Indian firms.

2.1. **Data.** We use annual data on manufacturing firms from the Indian Annual Survey of Industry (ASI), which is conducted by the Indian Ministry of Statistics and Programme Implementation, and is the Indian government's main source of industrial statistics on the formal manufacturing sector. The ASI consists of two parts: a census of all manufacturing plants that are larger than 100 employees, and a random sample of one fifth of all plants that employ between 20 and 100 workers. The ASI's sampling methodology and product classifications have changed several times over the course of its history. In order to ensure consistency, we focus on the time frame of the fiscal years (May to April) 2000/01 to 2007/08.

The crucial aspect of the ASI is that it contains detailed information on both intermediate inputs and outputs at the plant level, which allows us to link the firm's input characteristics to their product mix decisions. This, in particular, distinguishes the ASI from two other datasets that have been used to study product turnover: the

US Census Bureau's Longitudinal Business Database, used by Bernard et al. (2010a) (henceforth BRS), and the Prowess database, published by the Centre for Monitoring the Indian Economy and used by Goldberg et al. (2009) (henceforth GKPT) to document product turnover among Indian manufacturing firms. Compared to the ASI, the Prowess database contains only information on listed firms.

2.2. **Definition of Products.** At their finest levels, BRS have 1,440 5-digit SIC products for US firms in 455 4-digit industries belonging to 20 2-digit SIC sectors. GKPT have 1,886 "products" under 108 4-digit NIC industries in 22 2-digit NIC sectors. Compared to them, ASI has 5,204 5-digit ASIC products at the finest level. A broader 4-digit code contains 1,108 distinct products which is roughly comparable with the finest levels reported in BRS and GKPT. These products are in 262 3-digit ASIC industries, which will be our unit of analysis for the IO matrix. The products can be further aggregated to 64 2-digit sectors or 9 1-digit sectors.

2.3. **Product Turnover Among Indian Manufacturing Firms.** This section describes the nature of product turnover in multiproduct Indian firms.

2.3.1. *Multi-Product Firms Dominate Production.* Table 1 shows the prevalence of multi-product firms in our sample. Multi-product firms account for 39% of observations at the 4-digit level (41% if products are defined at the 5-digit level), similar to BRS and GKPT's datasets (39% and 47%, respectively). As is well known, multi-product firms tend to be larger: they account for 71% of sales. Multi-sector firms account for 19% (2-digit) and 8% (1-digit) of the observations in the sample, but 49% (32% respectively) of sales.

Table 1. Frequency and Sales Shares of Single and Multi-product Firms

# of Products/Industries	5-digit Obs	5-digit % Firms	5-digit % Sales	4-digit Obs	4-digit % Firms	4-digit % Sales	3-digit Obs	3-digit % Firms	3-digit % Sales
1	15946	58.6	28.7	159873	**61.2**	**30.4**	176882	67.8	37.8
2	53859	20.6	20.4	56503	21.6	21.5	54777	21.0	24.1
3	26864	10.3	12.4	24460	9.4	14.4	19430	7.4	13.3
4	14477	5.5	8.6	11413	4.4	9.7	5869	2.2	8.0
5	6183	2.4	7.4	4585	1.8	5.7	2415	0.9	5.3
6	3028	1.2	3.7	2134	0.8	4.3	1030	0.4	5.8
7	1678	0.6	3.7	1085	0.4	5.6	441	0.2	2.2
8	1050	0.4	3.3	599	0.2	3.6	139	0.1	1.1
9	641	0.2	4.9	299	0.1	2.0	51	0.0	0.6
10+	331	0.1	7.1	106	0.0	2.7	23	0.0	1.8

# of Products/Industries	2-digit Obs	2-digit % Firms	2-digit % Sales	1-digit Obs	1-digit % Firms	1-digit % Sales
1	212420	81.4	50.7	239970	91.9	68.3
2	36568	14.0	28.4	19219	7.4	27.3
3	8608	3.3	12.2	1683	0.6	4.1
4	2523	1.0	5.0	168	0.1	0.3
5	717	0.3	2.0	15	0.0	0.0
6	180	0.1	1.6	2	0.0	0.0
7	34	0.0	0.0			
8	5	0.0	0.0			
9	2	0.0	0.0			
10+						

Source: Author's calculations from ASI data.

GKPT's sample of publicly listed firms in India during the nineties gives similar results, 24% of firms are multi-sector firms and their share in total sales is 54%. Table 2 compares sales shares in our sample with GKPT.

Table 2. Comparison of Multiproduct Firms in GKPT and ASI

	Share of Firms		Share of Output		Mean #Products	
Type of Firm	ASI	GKPT	ASI	GKPT	ASI	GKPT
Multiple 4-digit Products	0.39	0.47	0.70	0.80	2.81	3.06
Multiple 3-digit Products	0.22	0.33	0.62	0.62	2.55	2.01
Multiple 2-digit Products	0.19	0.24	0.49	0.54	2.34	1.68

Note: 'Mean #Products' refers to the average number of products in the respective subsample.

2.3.2. *Firms Focus on Their Core Competencies.* Table 3 shows the sales distribution of products within firms. The fact that the firms generate a large proportion of its sales revenue from its primary products suggests that firms have 'core competencies'. The concentration of sales is similar to the findings of GKPT (Table 3) that uses the CMIE data on publicly listed firms, so we are confident of the soundness of the data.

Table 3. Average Sales Shares by Product Rank

	4-digit Products in ASI											GKPT Products									
Rank	1	2	3	4	5	6	7	8	9	10	Rank	1	2	3	4	5	6	7	8	9	10+
1	100	87	78	72	62	57	54	51	46	44	1	100	86	75	70	65	63	62	64	53	44
2		13	17	18	21	22	22	20	20	20	2		14	20	21	21	21	19	16	22	20
3			5	7	10	11	11	12	12	11	3			4	7	9	9	9	9	12	13
4				2	5	6	64	7	8	8	4				2	4	4	6	5	7	7
5					2	3	4	5	5	6	5					2	2	3	3	3	4
6						1	2	3	4	4	6						1	1	2	2	3
7							1	2	3	3	7							0	1	1	2
8								1	2	2	8								0	1	2
9									1	1	9									0	1
10+										1											2

Note: Columns indicate the number of products, rows indicate the rank of the product.

2.3.3. *Product Turnover is Prevalent.* We now turn to documenting product and industry turnover among the ASI firms. To study the determinants of product turnover, we will examine how firms add products across different ASIC industries. Table 4 shows the fraction of firms that change their product scope over a one-year, three-year, and five-year horizon. Given the nature of the ASI sampling methodology, our panel is not balanced; an n-year horizon hence consists of all observation pairs that are n

Table 4. Product Turnover

		Percentage of Firms												Sales-Weighted Percentage of Firms											
		1-year horizon				3-year horizon				5-year horizon				1-year horizon				3-year horizon				5-year horizon			
		no activity	add only	drop only	add and drop	no activity	add only	drop only	add and drop	no activity	add only	drop only	add and drop	no activity	add only	drop only	add and drop	no activity	add only	drop only	add and drop	no activity	add only	drop only	add and drop
	single	93	4		3	92	5		4	91	5		4	93	6		1	92	7		1	91	7		1
1-digit	multi	51	4	38	7	40	4	48	8	34	3	53	9	59	5	25	11	58	5	30	7	56	4	36	4
	all	89	4	4	4	86	4	5	4	85	5	6	5	81	5	9	5	80	6	10	3	80	6	12	2
	single	84	7		10	81	8		11	79	9		12	89	7		4	89	7		4	89	7		4
2-digit	multi	41	7	31	21	30	7	38	24	26	7	42	25	41	9	27	23	35	10	34	22	35	6	40	19
	all	74	7	7	12	69	8	9	14	66	9	11	15	64	8	14	14	61	8	18	13	62	6	20	12
	single	75	8		17	70	11		19	68	12		20	86	7		7	85	8		7	84	8		8
3-digit	multi	36	8	24	33	26	8	29	36	22	8	31	39	29	10	25	37	23	14	26	38	22	9	34	36
	all	62	8	8	22	54	10	11	25	51	10	12	27	48	9	16	27	44	12	17	27	43	9	22	26
	single	63	7		30	56	10		35	52	11		37	80	5		15	79	6		15	77	7		16
4-digit	multi	26	6	16	51	18	7	20	56	15	6	21	58	23	6	17	54	16	11	17	56	15	6	20	59
	all	47	7	7	39	39	8	9	44	35	9	10	47	39	5	12	44	33	10	12	45	32	6	15	47

Note: Numbers in the table are the percentage of firm-year observations that fall in the respective category. Product additions and drops are defined forward-looking, i.e. if a firm has one product in year 2001, and sells the same product plus an additional one in year 2002, this would count as one observation in the "add only" category in 2001 (also, it would count as a single-product firm). Hence, by definition, single-product firms cannot only drop a product.

years apart from each other. The product scope changes are forward-looking: a plant that produces one product in year t and the same product together with a new one in year $t+1$ would be counted as an 'add only' for a single-product firm at the one-year horizon. Looking at the 4-digit ASIC category, we find that 65% of all firms make some change in their product range in a 5-year horizon. The corresponding number for 3-digit products is 57%, showing that product churning is highly prevalent.

2.3.4. *Product Churning Rates are Similar to US Firms.* One fact that emerges is that product turnover in the ASI data is broadly similar to BRS. Looking at the comparable 4-digit ASIC category, we find that 65% of all firms make some change in their product range in a 5-year horizon, compared to 54% of firms in BRS. For multi-product firms, this difference is smaller: 85% in the ASI data compared with 80% in BRS. The main difference is a higher percentage of multiproduct firms drop products in the ASI than BRS, but this difference is small when the prevalence is weighted by firm sales. Compared to BRS, we find that fewer firms add and drop products, leading to higher levels of no activity firms when weighted by firm sales.

Another fact that emerges is that product turnover in the ASI data is higher than in GKPT. Even looking at the highly aggregate 2-digit ASIC category (which has 64 product categories), we find that 26% of all firms make some change in their product range. GKPT find instead that only 10% of firms engage in product range changes where the product is the finest level of aggregation which has 1,500 product categories. For multi-product firms, this difference is even wider: 59% in the ASI data compared with 14% in GKPT. These differences are also present for both the subset of sample firms of the ASI and the subset of census ASI firms. Compared to GKPT, we also find higher levels of product dropping. In our sample, 7 percent of all firms drop products (4-digit) without adding new ones in the same year. The figure is higher over a three-year horizon (9%) and five-year horizon (10%). In GKPT's sample, only 2% of firms drop products without adding new ones (3% and 5% over a three-year and five-year horizon). The right panel of Table 5 weighs the fractions of product-changing firms by their sales revenue. Twelve percent of sales revenue gets dropped at an annual frequency without being replaced by a new product in the same period (in GKPT's sample, the corresponding fraction is three percent).[5]

[5]The fact that many firms seem to be replacing existing products by new ones raises concerns about the quality of the reported product codes. If plant managers are inconsistent over time in their reporting of product codes, the true fraction of firms that is either adding or dropping products would be higher than the observed fraction of firms. Hence, our estimates of the prevalence of product additions or droppings are lower bounds for the true number. Note also that misreporting of product codes is likely to be washed out as we aggregate products to three-digit industries and one- or two-digit sectors.

Table 5. Product Turnover Over A Five-Year Horizon

		% of Firms				Sales-wtd. % of Firms			
		no activity	add only	drop only	add & drop	no activity	add only	drop only	add & drop
4-digit	single	52	11		37	77	7		16
	multi	15	6	21	58	15	6	20	59
	all	35	9	10	47	32	6	15	47
GKPT	single	80	19		1	76	24		0
	multi	63	26	8	3	53	29	3	15
	all	72	22	4	2	57	28	2	12
BRS	single								
	multi	20	32	12	36	6	12	8	75
	all	46	14	15	25	11	10	10	68

Note: Numbers in the table are the percentage of firm-year observations that fall in the respective category. Product additions and drops are defined forward-looking, i.e. if a firm has one product in year 2001, and sells the same product plus an additional one in year 2002, this would count as one observation in the "add only" category in 2001 (also, it would count as a single-product firm). Hence, by definition, single-product firms cannot only drop a product. Rows “BRS” are reproduced from Table 3 in Bernard et al. (2010b). Rows “GKPT” are reproduced from Table 4 in Goldberg et al. (2009).

3. Input-Output Linkages and Product Adoption

In this section, we document a robust relationship between a firm’s input-output linkages and the direction of product adoption: firms are more likely to add products that are either horizontally or vertically related to their existing product line. Our evaluation uses firm level data on transfers to suppliers (expenditures) and from buyers of a firm’s products (sales). Firms are more likely to add products in industries:

- which exhibit similar distributions of expenditures or sales, or,
- which are vertically related as inputs or outputs.

We then show that controlling for the rates at which each firm’s main product adopts every other product each period, these patterns still hold. Additionally, evidence using product dereservation in conjunction with these controls isolates the mechanisms of these four possible input-output channels. Our estimates of the impact of dereservation show that horizontal and vertical *upstream* linkages, and thus economies of scope, are the strongest driver of product adoption.

3.1. **Horizontal Linkages: Input and Output Similarity.** Do firms have inherent horizontal product capabilities, such as economies of scope or strategic complementarities across products? To answer this, we can predict product adoption with increasingly strict controls, and use idiosyncratic firm characteristics to understand product adoption. Accordingly, to understand if idiosyncratic economies of scope drive product adoption, we define a firm's input similarity to a sector. Similarly, to understand if product market complementarities drive adoption, we define a firm's output similarity to a sector.

To define these similarity measures, we consider a firm j as having a type composed of two vectors:

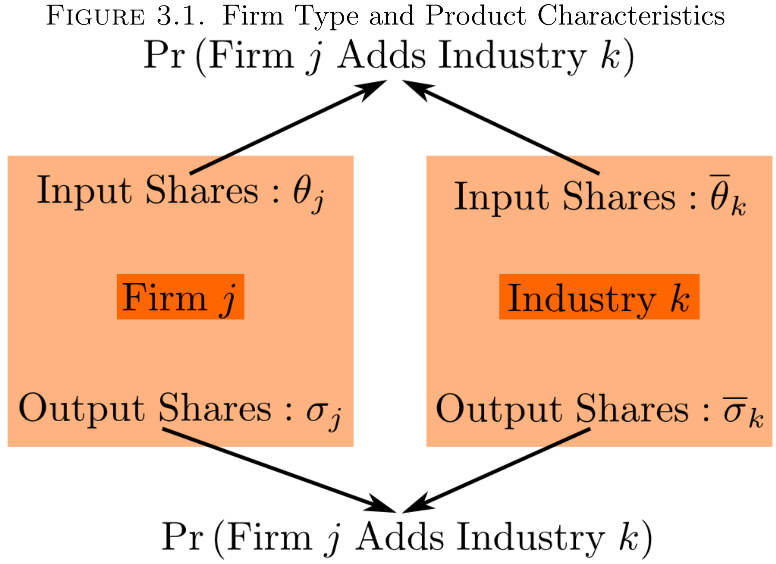
- The vector of input expenditure shares the first time it is observed, θ_j.
- The vector of output sales shares the first time it is observed, σ_j.

We generalize a firm's type to a high dimensional 'fingerprint' of input and output capabilities. By expressing a firm's type in relation to different characteristics of products, we can test how firm and product characteristics are complements. We also consider each product k as having characteristics composed of two vectors derived from a national Input-Output table:

- The vector of aggregate input expenditure shares, $\overline{\theta}_k$.
- The vector of aggregate output sales shares, $\overline{\sigma}_k$.

Using a firm's type and product characteristics, *horizontal similarity* through common purchases of inputs or common sales of outputs could predict product adoption as in Figure 3.1.

FIGURE 3.1. Firm Type and Product Characteristics



A natural candidate to determine the similarity of a firm's input or output type and a product's input or output characteristics is the normalized dot product which measures the common 'direction' of these types in a high dimensional space.[6] Our measure of input similarity is therefore defined as:

$$\text{inputSimilarity}_j^k = \sum_{n=1}^{N} \theta_{jn}\overline{\theta}_{kn} \Big/ \sqrt{\left(\sum_{n=1}^{N} \theta_{jn}^2\right)\left(\sum_{n=1}^{N} \overline{\theta}_{kn}^2\right)}$$

where n indexes expenditure shares of spending on three-digit inputs. We construct aggregate intermediate input shares by aggregating up the micro-data, treating a plant as belonging to the three-digit sector where the value of its produced goods is the highest. $\text{inputSimilarity}_j^k$ ranges from zero when firm j and sector k have no three-digit inputs in common to one when the input expenditure shares of firm j and sector k are identical.[7] $\text{inputSimilarity}_j^k$ captures production complementarities such as economies of scope that incorporate groups of products to varying degrees.

Products might have product market complementarities, such that firms who produce one (or certain sets of products) are thereafter more likely to start producing another.[8] Analogous to our input similarity index, we construct an output similarity index $\text{outputSimilarity}_j^k$ as the normalized inner product between firm j's sales and product k's sales shares:

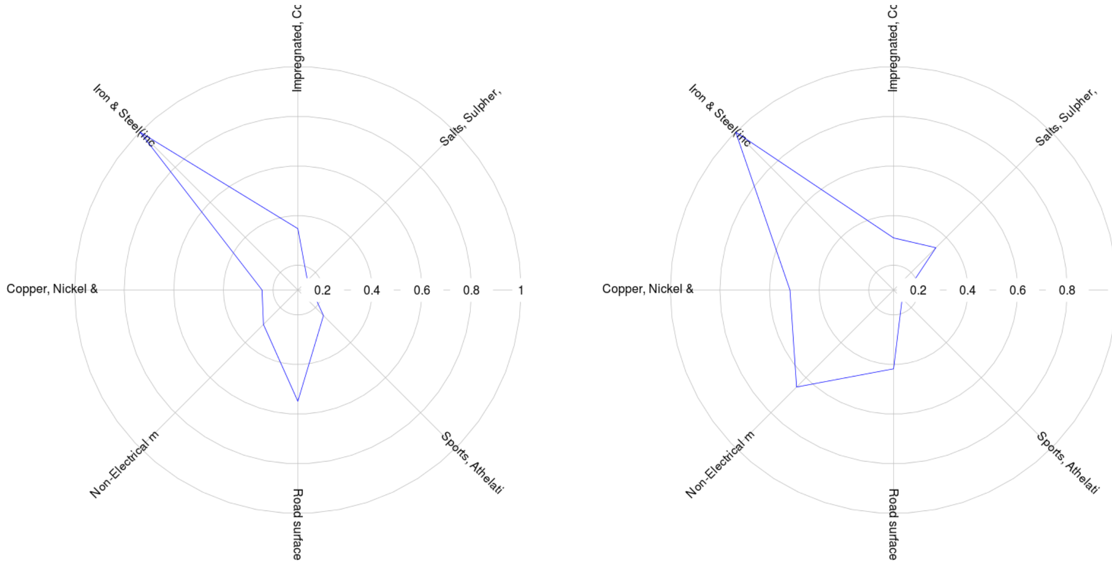
$$\text{outputSimilarity}_j^k = \sum_{n=1}^{N} \sigma_{jn}\overline{\sigma}_{kn} \Big/ \sqrt{\left(\sum_{n=1}^{N} \sigma_{jn}^2\right)\left(\sum_{n=1}^{N} \overline{\sigma}_{kn}^2\right)},$$

where n indexes the three-digit product code of firm sales and product purchasers.

Input similarity for the Iron and Steel industry as a whole is depicted in Figure 3.3a for all industries with a similarity greater than .1. In contrast, output similarity for the Iron and Steel industry is depicted in Figure 3.3b for all industries with a similarity greater than .1. In both cases, similarity with Iron and Steel is 1, while output similarity is more concentrated than input similarity.

[6]This approach to horizontal relatedness is distinct from 'circular flows' between industries (e.g. Fan and Lang (2000a)).
[7]We use the normalized dot product for this measure, as otherwise a firm which has multiple identical inputs as a product would have a similarity measure of less than one.
[8]Bernard et al. (2010a) document a sizable amount of co-production particularly between textile and apparel producers, and between machinery, metal, and electronics producers.

FIGURE 3.2. Similarity for the Iron and Steel Industry



(A) Input Similarity (B) Output Similarity

While our input and output similarity measures focus on similar distributions of inputs or outputs, other important directions firms' product lines might move is up and down their value chain, for which we next define measures of vertical linkages.

3.2. **Vertical Linkages: Expected Upstream and Downstream Shares.** An important theme in economic growth and development is that firms expand along their value chain and incorporate the production of upstream and downstream products in house. Do vertical linkages predict product adoption? To answer this, we can control for the rate at which firms who make one product adopt other products, and use the idiosyncratic vertical linkages of firms to understand product adoption. Accordingly, we define *vertical similarity* through the expected upstream expenditures and expected downstream sales of a firm j for product k as:

$$\text{expectedUpstream}_j^k = \sum_{n=1}^{N} \sigma_{jn}\overline{\theta}_{kn}, \qquad \text{expectedDownstream}_j^k = \sum_{n=1}^{N} \theta_{jn}\overline{\sigma}_{kn}. \tag{3.1}$$

Equation (3.1) predicts upstream purchases as in the following analogy: imagine a firm j where what is observed is the sales shares of the firm, σ_j, and the goal is to predict the expenditures of the firm knowing only the national input-output table. Given the average expenditures made producing product k, $\overline{\theta}_k$, one would expect the expenditure share of each input to be $\text{expectedUpstream}_j^k$. The interpretation of $\text{expectedDownstream}_j^k$ is similar.

3.3. **Estimating the Role of Horizontal and Vertical Linkages.** The two measures of horizontal similarity, $\text{inputSimilarity}_j^k$ and $\text{outputSimilarity}_j^k$ and two measures of vertical similarity, $\text{expectedUpstream}_j^k$ and $\text{expectedDownstream}_j^k$, can be used to predict product addition through the following linear probability model:

$$\begin{aligned} \text{Add}_{jt}^k = {} & \beta^{\text{in}} \cdot \text{inputSimilarity}_j^k + \beta^{\text{out}} \cdot \text{outputSimilarity}_j^k \\ & + \beta^{\text{up}} \cdot \text{expectedUpstream}_j^k + \beta^{\text{down}} \cdot \text{expectedDownstream}_j^k \\ & + \alpha_{jt} + \alpha_t^k + \alpha_t^{kk'} + \varepsilon_{jt}^k \end{aligned} \tag{3.2}$$

where the remaining undefined variables in this specification are:

- Add_{jt}^k is one if firm j adds a 3-digit industry k at time t.
- α_{jt} is a Firm-Time Fixed Effect which captures the rate of product adoption for each firm-year, leaving only the *direction* of product change.
- α_t^k is a Product-time Fixed Effect which captures any economic changes that impact the adoption of each product and period.
- $\alpha_t^{kk'}$ is a Product-Industry Fixed Effect where k' is the main product of firm j which captures economic changes that might impact the adoption of each product by an industry.
- ε_{jt}^k is an idiosyncratic error term at the level of Firm-Product-Time.

3.4. **Summary Statistics.** We start with descriptive statistics for the variables in Equation (3.2) in Tables 6 and 7, and then we present the estimation results.

Table 6. Summary Statistics

Description	Obs	Mean	Std. Dev.	Min	Max
Added a 3-digit product	61,205,507	0.0007	0.026	0	1
Input Similarity Index	61,205,507	0.0359	0.122	0	.99
Output Similarity Index	61,205,507	0.0053	0.064	0	1
Expected Upstream Index	61,205,507	0.0040	0.035	0	.99
Expected Downstream Index	61,205,507	0.0040	0.049	0	1

Table 7. Correlation of IO Similarity Indexes

	IS	OS	Up	Down
Input Similarity	1			
Output Similarity	0.31	1		
Expected Upstream	0.31	0.50	1	
Expected Downstream	0.35	0.36	0.65	1

Table 8 shows the results of predicting product adoption, with the inclusion of increasingly stringent fixed effects from left to right. The first specification contains no fixed effect except for a constant, is remarkably stable across the first three specifications. The second specification includes Firm-Time fixed effects which estimate the rate of product adoption for each firm every period, leaving only estimates of the *direction of production adoption* for each firm, showing that all four IO linkages influence direction. The third specification additionally includes product level fixed effects for every period which remove any systematic demand or supply shocks that could impact individual product adoption.

The fourth specification of Table 8 is very stringent, in that it includes an estimated rate of product adoption for each product *and* the main industry of each firm (measured by sales) *for each period*. This means that any economic shocks (supply, demand, technology, infrastructure, etc.) that might affect the product co-occurrence emphasized heavily in the literature is accounted for and what remains are estimates of the direction of intra-industry product changes driven by idiosyncratic IO linkages of each firm. As the Table shows, all four linkages remain important even in this specification.

Table 8. Product Addition: Horizontal and Vertical Linkages

Dependent variable: Product Addition Dummy$_{jt}^{k}$	(1)	(2)	(3)	(4)
inputSimilarity$_j^k$	0.008***	0.008***	0.008***	0.004***
	(.00003)	(.0001)	(.0001)	(.0002)
outputSimilarity$_j^k$	0.009***	0.008***	0.008***	0.027***
	(.00006)	(.0003)	(.0003)	(.0021)
expectedUpstream$_j^k$	0.013***	0.013***	0.012***	0.009***
	(.00014)	(.00066)	(.00066)	(.00485)
expectedDownstream$_j^k$	0.005***	0.005***	0.005***	0.008***
	(.00009)	(.00045)	(.00045)	(.00050)
Firm-Year FE α_{jt}	no	yes	yes	yes
Product-year FE α_t^k	no	no	yes	no
Industry-Product-Year FE $\alpha_t^{kk'}$	no	no	no	yes
R^2	0.004	0.010	0.011	0.038

Our preferred specification is presented in column 3 of Table 8, which controls for annual rates of product adoption at the firm level in addition to annual supply and demand shocks that occur at the product level. These estimates can be quantified in comparison with the mean product adoption rate of .07 percent: the effect of a one standard deviation increase in each of the input-output linkage measures as a percentage of mean product adoption is reported in Table 9.

Table 9. Input-Output Linkages and Product Adoption Rates

Horizontal Measures		Vertical Measures	
inputSimilarity$_j^k$	146%	expectedUpstream$_j^k$	68%
outputSimilarity$_j^k$	86%	expectedDownstream$_j^k$	37%

Three things are worth noting from Table 9:

- All four input-output measures are quantitatively significant.
- Horizontal measures explain more product adoption than vertical measures.
- Upstream measures explain more product adoption than downstream measures.

However, whether these idiosyncratic linkages interact with the economic environment to subsequently change the direction of production adoption is less clear. We turn to this question next.

3.5. **The Impact of Dereservation.** While the four measures of horizontal and vertical similarity have been shown above to predict the direction of product adoption, it is unclear to what extent it is these firm characteristics specifically that drive adoption. However, we can disentangle the role of these characteristics by examining the effect of product reservation on a firm's input and output use. We start with a discussion of the policy change and then discuss estimation using the variation in policy.

3.5.1. *Product Dereservation.* The small scale sector in India contributes almost 40% to gross industrial value-added and is the second largest employer after agriculture. The development of SSI has been a national priority in economic planning. To achieve this, India implemented a policy of reservation of certain products for exclusive manufacture by SSI firms. The policy to reserve certain products was put in place to ensure employment expansion, a more equitable distribution incomes and "greater mobilization of private sector resources of capital and skills."[9] Reservation of products for exclusive manufacture in the small scale sector was introduced for the first time in 1967 with the reservation of 47 items. This number increased progressively as in Table 10.

TABLE 10. Reservation of Products

Year	1970	1971	1971	1974	1976	1978
Number of Products Reserved	55	128	124	177	180	504

After the introduction of the National Industrial Classification (NIC) system, the list was revised. The list expanded from 504 to 807 in 1978 and then to 836 in 1989. Out of this, the following number of items were de-reserved over the years, as in Table 11. The definition of small scale industries (SSI) has been changed continually. In 1955, SSI was defined as establishments with fixed investments of less than Rs 500,000 which employed less than 50 workers when working with power or less than 100 workers when not working with power. The employment criterion was dropped in 1960, and the SSI definition was based on the original value of investment in plant and machinery. The investment value was revised over time, and by 1999, the investment ceiling was Rs 10 million in plant and machinery (at historical cost).

[9]http://www.dcmsme.gov.in/ssiindia/MSME_OVERVIEW09.pdf.

Table 11. Dereservation of Products

Year	1997	1999	2001	2002	2003	2004	2005	2006	2007	2008
Number of Products Dereserved	15	9	15	51	75	85	108	180	212	107

According to the expert committee set up by the government to look into small scale industries, reservation did little to promote small enterprises and had negative consequences by keeping out large enterprises. With free imports of most goods post liberalization, the reservation policy was no longer relevant. It also did not cover the large majority of products manufactured by the small scale sector. Those industries that were covered such as light engineering and food processing were unable to grow and invest in better technologies due to the limitations imposed by SSI reservation. Consequently, the government was repeatedly advised to dereserve products from the SSI list.[10] The policy to dereserve products from the SSI list has recently been used by Martin et al. (2014) to study the employment generation ability of small enterprises. They also explain that the selection criterion mentioned in official documents was the ability of SSIs to manufacture these products, and that the choice of products was "arbitrary" according to official accounts (Hussain 1997; Mohan 2002).

The impact of dereservation on product expenditure and sales is estimated in Table 12. At the level of the intensive margin within a firm, the impact of a product being dereserved on expenditures was an increase of 3%, while dereservation of a product decreased subsequent sales by 13%, presumably through increased competition in the market for the product. The next sub-section uses the change in the reservation policy as a channel to isolate the effect of horizontal and vertical linkages across products.

Table 12. The Impact of Dereservation on Product Expenditure and Sales

	Input Expenditure$^k_{jt}$	Output Sales$^k_{jt}$
	(1)	(2)
DeReserve^k_t	0.0305**	-0.1360***
	(.0141)	(.0410)
Firm-Year FE α_{jt}	yes	yes
Firm-Industry FE α^k_j	yes	yes
N	477,133	203,239
R^2	0.922	0.890

Notes:** 5%, *** 1% levels of significance.

[10]http://www.isedonline.org/uploads/userfiles/file/file/Report%20of%20the%20Expert%20Committee%20on%20Small%2

3.5.2. *Horizontal and Vertical Linkages with Policy Variation.* We build up measures of horizontal and vertical input-output similarity using dereservation as a source of variation to estimate their impact on product adoption. Specifically, letting δ_t^n be one in the year a product is dereserved and thereafter, we can define the following measures of IO linkages that additively augment the four measures already defined:

$$\begin{aligned}
\text{DereserveInputSim}_{jt}^k &= \sum_{n=1}^N \delta_t^n \theta_{jn} \overline{\theta}_{kn} / \sqrt{\left(\sum_{n=1}^N \theta_{jn}^2\right)\left(\sum_{n=1}^N \overline{\theta}_{kn}^2\right)}, \\
\text{DereserveOutputSim}_{jt}^k &= \sum_{n=1}^N \delta_t^n \sigma_{jn} \overline{\sigma}_{kn} / \sqrt{\left(\sum_{n=1}^N \sigma_{jn}^2\right)\left(\sum_{n=1}^N \overline{\sigma}_{kn}^2\right)}, \\
\text{DereserveExpUp}_{jt}^k &= \sum_{n=1}^N \delta_t^n \sigma_{jn} \overline{\theta}_{kn}, \\
\text{DereserveExpDown}_{jt}^k &= \sum_{n=1}^N \delta_t^n \theta_{jn} \overline{\sigma}_{kn}.
\end{aligned}$$

These measures 'select' the portion of each of the above IO linkage measures to the subset that have been dereserved. Increased dereservation should amplify the role of inputs (increased availability) and outputs (easier adoption of products, or complementary products). Then the following specification can predict product addition a linear probability model:

$$\begin{aligned}
\text{Add}_{jt}^k = {} & \beta^{\text{in}} \cdot \text{inputSimilarity}_j^k + \beta^{\text{out}} \cdot \text{outputSimilarity}_j^k \\
& + \beta^{\text{up}} \cdot \text{expectedUpstream}_j^k + \beta^{\text{down}} \cdot \text{expectedDownstream}_j^k \\
& + \gamma^{\text{in}} \cdot \text{DereserveInputSim}_{jt}^k + \gamma^{\text{out}} \cdot \text{DereserveOutputSim}_{jt}^k \\
& + \gamma^{\text{up}} \cdot \text{DereserveExpUp}_{jt}^k + \gamma^{\text{down}} \cdot \text{DereserveExpDown}_{jt}^k \\
& + \alpha_{jt} + \alpha_t^k + \alpha_t^{kk'} + \varepsilon_{jt}^k
\end{aligned} \tag{3.3}$$

where the fixed effects are defined as above. The descriptive statistics for the dereservation variables in Equation 3.3 are summarized in Table 14 and the correlation between the RHS variables is shown in Table 13. We find that using the policy variation substantially lowers the correlation across different measures of horizontal and vertical linkages.

Table 13. Summary Statistics - Dereservation

Description	Obs	Mean	Std. Dev.	Min	Max
Dereserved Input Similarity	61,205,507	0.0005	0.013	0	.99
Dereserved Output Similarity	61,205,507	0.0001	0.011	0	.99
Dereserved ExpUpstream	61,205,507	0.0001	0.005	0	.93
Dereserved ExpDownstream	61,205,507	0.0001	0.005	0	.99

Table 14. Correlation - Dereservation

	IS	OS	Up	Down	De·IS	De·OS	De·Up
Input Similarity	1						
Output Similarity	0.31	1					
Expected Upstream	0.31	0.50	1				
Expected Downstream	0.35	0.36	0.65	1			
Dereserved Input Similarity	0.11	0.04	0.03	0.10	1		
Dereserved Output Similarity	0.05	0.17	0.04	0.03	0.05	1	
Dereserved ExpUpstream	0.06	0.06	0.15	0.10	0.05	0.30	1
Dereserved ExpDownstream	0.04	0.04	0.06	0.11	0.34	0.10	0.10

3.5.3. *Estimation Results with Policy Variation.* Table 15 contains the results of estimating Equation (3.3). The estimates for the four IO linkage measures are very stable: they are almost identical to those above. The four IO linkage measures using dereservation are all positive and significant (except in the last, most stringent specification) showing that as the influence of each IO linkage is increased at the firm level, they amplify the rate of product adoption in the direction estimated above. This provides sharp evidence of each of the linkage mechanisms since dereservation amplifies them. As reported in Tables 17 and 19 of the Appendix, these estimates are robust to varying definitions of the time lags for dereservation and to constructing the Input-Output Table using only single product firms.

Table 15. Product Addition: The Impact of Dereservation

Dependent variable: Product Addition Dummy$_{jt}^{k}$	(1)	(2)	(3)	(4)
inputSimilarity$_{j}^{k}$	0.008***	0.008***	0.008***	0.004***
	(.00012)	(.00011)	(.00012)	(.00017)
outputSimilarity$_{j}^{k}$	0.008***	0.008***	0.008***	0.027***
	(.00032)	(.00032)	(.00032)	(.00210)
expectedUpstream$_{j}^{k}$	0.012***	0.012***	0.012***	0.008**
	(.00066)	(.00066)	(.00066)	(.00486)
expectedDownstream$_{j}^{k}$	0.005***	0.005***	0.005***	0.008***
	(.00046)	(.00046)	(.00046)	(.00051)
DereserveInputSim$_{jt}^{k}$	0.006***	0.006***	0.007***	0.006***
	(.00134)	(.00137)	(.00137)	(.00132)
DereserveOutputSim$_{jt}^{k}$	0.007***	0.007***	0.007***	0.004**
	(.00178)	(.00178)	(.00178)	(.00215)
DereserveExpUp$_{jt}^{k}$	0.022***	0.022***	0.021***	0.019***
	(.00363)	(.00364)	(.00363)	(.00404)
DereserveExpDown$_{jt}^{k}$	0.012***	0.012***	0.012***	-0.001
	(.00367)	(.00368)	(.00367)	(.00368)
Firm-Year FE α_{jt}	no	yes	yes	yes
Product-year FE α_{t}^{k}	no	no	yes	no
Industry-Product-Year FE $\alpha_{t}^{kk'}$	no	no	no	yes
R^2	0.004	0.010	0.011	0.038

Our preferred specification corresponds to column 3 of Table 15.[11] As above, these estimates can be quantified in comparison with the mean product adoption rate of .07 percent: the effect of a one standard deviation increase in each of the input-output linkage measures as a percentage of mean product adoption is reported in Table 16.

[11]Similar estimates obtain when restricting the sample to the larger firms which appear in the Census Sector of the ASI, as reported in Table 18 of the Appendix.

TABLE 16. Input-Output Linkages, Dereservation and Product Adoption Rates

Horizontal Measures		Vertical Measures	
$\text{inputSimilarity}_j^k$	146%	$\text{expectedUpstream}_j^k$	68%
$\text{outputSimilarity}_j^k$	86%	$\text{expectedDownstream}_j^k$	37%
$\text{DereserveInputSim}_{jt}^k$	12%	$\text{DereserveExpUp}_{jt}^k$	14%
$\text{DereserveOutputSim}_{jt}^k$	7%	$\text{DereserveExpDown}_{jt}^k$	0%

Three things are worth noting from Table 16:

- All eight input-output measures are quantitatively significant.
- The magnitudes of the dereservation estimates which pinpoint IO linkages as a mechanism are much smaller.
- Upstream measures explain more product adoption than downstream measures.

4. Conclusion

This paper estimates how horizontal and vertical linkages at the firm level determine how firms move in the product space. Firms' product scope and turnover are crucial and dynamic aspects of microeconomic behavior, yet there is little concrete evidence of the direction of product diversification. This paper has established that horizontal and vertical linkages are important factors in these decisions and that firms are more likely to add products that have idiosyncratic upstream linkages. While we provide microeconometric evidence of capability theories of the firm, it remains a challenge to model and empirically test the ultimate sources of such capabilities (Andreoni, 2014). In that regard, what we have shown is that even controlling for the rates at which firms in a particular industry adopt every other industry's products, idiosyncratic input patterns predict product adoption the most strongly. This points further studies of product choice towards firms' upstream connections and suggests policy will be most effective when focused on the provision of intermediate inputs.

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Appendix A. Robustness of Estimates

Table 17 recaps our estimates of the joint effect of horizontal and vertical similarity along with dereservation in column 1. Column 2 reports estimates of an altered specification: in this case, the effect of product reservation δ_t^n is only included if the firm bought (for upstream measures) or sold (for downstream measures) the product in the year of dereservation or before. Similarly, column 3 estimates the effect of dereservation if the firm bought or sold the product strictly before the year of dereservation. Table 17 shows the results are very comparable across specifications. Table 19 also shows the results are very comparable when the Input-Output table is constructed using only data from single product firms.

Table 17. Product Addition: Robustness of Usage and Production Definitions

Dependent variable: Product Addition Dummy$_{jt}^k$	(1)	(2)	(3)
inputSimilarity$_j^k$	0.004***	0.004***	0.004***
	(.00017)	(.00017)	(.00017)
outputSimilarity$_j^k$	0.027***	0.027***	0.027***
	(.00210)	(.00211)	(.00211)
expectedUpstream$_j^k$	0.008**	0.008*	0.009**
	(.00486)	(.00486)	(.00485)
expectedDownstream$_j^k$	0.008***	0.008***	0.008***
	(.00051)	(.00051)	(.00051)
DereserveInputSim$_{jt}^k$	0.006***	0.003***	0.006***
	(.00132)	(.00118)	(.00142)
DereserveOutputSim$_{jt}^k$	0.004**	-0.000	0.015***
	(.00215)	(.00215)	(.00278)
DereserveExpUp$_{jt}^k$	0.019***	0.017***	0.020***
	(.00404)	(.00391)	(.00493)
DereserveExpDown$_{jt}^k$	-0.001	-0.004	-0.002
	(.00368)	(.00357)	(.00448)
Firm-Year FE α_{jt}	yes	yes	yes
Product-year FE α_t^k	no	no	no
Industry-Product-Year FE $\alpha_t^{kk'}$	yes	yes	yes
R^2	0.038	0.038	0.038

Table 18. Product Addition: The Impact of Dereservation (Census Only Sample)

Dependent variable: Product Addition Dummy$_{jt}^{k}$	(1)	(2)	(3)	(4)
inputSimilarity$_{j}^{k}$	0.013***	0.014***	0.013***	0.006***
	(.00006)	(.00023)	(.00024)	(.00031)
outputSimilarity$_{j}^{k}$	0.016***	0.015***	0.015***	0.046***
	(.00121)	(.00062)	(.00063)	(.00379)
expectedUpstream$_{j}^{k}$	0.021***	0.021***	0.020***	0.032***
	(.00261)	(.00129)	(.00128)	(.00903)
expectedDownstream$_{j}^{k}$	0.005***	0.005***	0.005***	0.011***
	(.00018)	(.00087)	(.00087)	(.00093)
DereserveInputSim$_{jt}^{k}$	0.005***	0.005***	0.006***	0.006***
	(.00045)	(.00194)	(.00193)	(.00180)
DereserveOutputSim$_{jt}^{k}$	0.007***	0.008***	0.008***	0.005
	(.00055)	(.00297)	(.00297)	(.00380)
DereserveExpUp$_{jt}^{k}$	0.028***	0.026***	0.026***	0.016**
	(.00119)	(.00587)	(.00585)	(.00686)
DereserveExpDown$_{jt}^{k}$	0.014***	0.013***	0.012**	-0.004
	(.00105)	(.00525)	(.00522)	(.00524)
Firm-Year FE α_{jt}	no	yes	yes	yes
Product-year FE α_{t}^{k}	no	no	yes	no
Industry-Product-Year FE $\alpha_{t}^{kk'}$	no	no	no	yes
R^2	0.003	0.010	0.011	0.038

Table 19. Product Addition: The Impact of Dereservation (Single Product IO Table)

Dependent variable: Product Addition Dummy$_{jt}^{k}$	(1)	(2)	(3)	(4)
inputSimilarity$_{j}^{k}$	0.009***	0.009***	0.009***	0.004***
	(.00003)	(.0001)	(.0001)	(.0002)
outputSimilarity$_{j}^{k}$	0.008***	0.008***	0.008***	0.027***
	(.0001)	(.0003)	(.0003)	(.0021)
expectedUpstream$_{j}^{k}$	0.012***	0.012***	0.011***	0.004
	(.0001)	(.0001)	(.001)	(.004)
expectedDownstream$_{j}^{k}$	0.004***	0.004***	0.004***	0.007***
	(.0001)	(.0005)	(.0005)	(.001)
DereserveInputSim$_{jt}^{k}$	0.005***	0.005***	0.006***	0.005***
	(.0003)	(.001)	(.001)	(.001)
DereserveOutputSim$_{jt}^{k}$	0.007***	0.007***	0.006***	0.003
	(.0003)	(.002)	(.002)	(.002)
DereserveExpUp$_{jt}^{k}$	0.017***	0.017***	0.017***	0.017***
	(.001)	(.003)	(.003)	(.004)
DereserveExpDown$_{jt}^{k}$	0.012***	0.012***	0.011***	-0.001
	(.001)	(.004)	(.004)	(.004)
Firm-Year FE α_{jt}	no	yes	yes	yes
Product-year FE α_{t}^{k}	no	no	yes	no
Industry-Product-Year FE $\alpha_{t}^{kk'}$	no	no	no	yes
R^2	0.004	0.010	0.011	0.038