Upstream, Downstream: Diffusion and Impacts of the Universal Product Code

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We study the adoption, diffusion, and impacts of the Universal Product Code (UPC) between 1975 and 1992, during the initial years of the bar code system. We find evidence of network effects in the diffusion process. Matched-sample difference-in-differences estimates show that

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firm size and trademark registrations increase following UPC adoption by manufacturers. Industry-level import penetration also increases with domestic UPC adoption. Our findings suggest that bar codes, scanning, and related technologies helped stimulate variety-enhancing product innovation and encourage the growth of international retail supply chains.

I. Introduction

The Universal Product Code (UPC) is widely touted as a major success of voluntary standardization. It was conceived in 1969 as a "standard human- [and machine-] readable code, to be used at all levels in the distribution channel" (Wilson 2001, 2). The UPC has been credited with increasing product selection in stores (Holmes 2001; Mann 2001), shifting the balance of power along the supply chain from manufacturers to retailers (Messinger and Narasimhan 1995), and stimulating labor productivity growth by promoting the rise of large retail chains (Sieling, Friedman, and Dumas 2001; Foster, Haltiwanger, and Krizan 2002).[1]

Although casual observation reveals that scanners and bar codes are ubiquitous in modern retail supply chains, there remains very little quantitative evidence of their effects. We provide new evidence on the diffusion and impacts of the UPC by linking archival data on UPC registrations to firm-level data on employment, revenue, and trademarking, as well as industry-level data on trade flows. Our findings illustrate the role of network effects in the adoption of the UPC system and suggest that bar codes, scanning, and related technologies helped stimulate variety-enhancing product innovation and encourage the growth of international retail supply chains.

Previous accounts of UPC diffusion have emphasized that bar codes originated within the grocery industry before spreading to general merchandising and other retail supply chains (Dunlop and Rivkin 1997). We examine the role of network effects within this diffusion process. Two-sided network effects imply that the return to adoption is higher for upstream producers supplying "UPC-ready" retailers and vice versa. Retailers become UPC ready by installing scanners and developing electronic data interchange (EDI) capabilities, including electronic payments (Abernathy et al. 1999; Basker 2012). Although we lack comprehensive data on scanner adoption, we provide indirect evidence of network effects by showing that there are positive spillovers in upstream UPC adoption. Specifically, manufacturers became more likely to register for a UPC when other manufacturing firms that use the same retail distribution channels also register.

[1] Tim Harford even named the bar code one of "50 Things That Shaped the Modern Economy." The other economy-shaping discoveries, inventions, and innovations include paper, the bicycle, and antibiotics. For his explanation of this choice, see http://www.bbc.co.uk/programmes/p04k0066.

After examining UPC diffusion, we study firm-level impacts of UPC adoption on employment, revenue, and trademarking, as well as the industry-level relationship between UPC adoption and international trade. Difference-in-differences regressions on a matched sample of UPC adopters and nonadopters from the manufacturing sector show that UPC registration is associated with increased revenue and employment. We discuss several possible mechanisms for this result, including that firms select into UPC registration because of anticipated demand shocks; that UPC registration coincides with adoption of a broader set of complementary technologies, such as EDI and inventory-control systems, which can increase demand or lower costs (Hwang and Weil 1998; Holmes 2001); and that UPC registration promotes growth through business diversion because retailers prefer to work with upstream vendors that have adopted bar codes. An event-study specification shows that manufacturer employment increased by 10% in the year of initial UPC registration and another 10% over the next 2 years. We argue that this pattern is consistent with a combination of selection on positive demand shocks and business diversion by manufacturers that can integrate into large retailers' supply chains more readily after registering for a UPC. We also show that the increases in revenue and employment following UPC registration are greater when there is more UPC adoption by other firms selling through the same retail channels, consistent with the presence of network effects.

Aggregate time-series data show that within the grocery industry, growth in trademark (TM) applications, new product introductions, and the number of stock-keeping units (SKUs) stocked by a typical supermarket all increased dramatically in the early 1980s, just as scanners were becoming widespread.[2] To study the relationship between UPC registration and product innovation, we exploit a new link between Census Bureau records and the US Patent and Trademark Office (USPTO) Trademark Case Files Dataset (Dinlersoz et al. 2021). Difference-in-differences and event-study regressions show that manufacturers became more likely to apply for TMs after registering for a UPC.

Finally, we merge our UPC adoption measure with industry-level data on US imports and exports (Feenstra 1996) to study the link between bar codes and trade. Difference-in-differences regressions show a substantial increase in import penetration within four-digit manufacturing industries where there is more domestic UPC adoption. This finding suggests that as retailers adapted to the UPC—by adopting complementary technology, such as scanners, EDI, and automated inventory control; carrying a greater variety of products; and even changing store formats—they were more likely to add international suppliers.

[2] SKUs are alphanumeric codes that track individual product data at a very granular level within a retail organization. UPCs, which can be used as SKUs, are standardized to allow for interfirm communication and coordination.

Our investigation of the diffusion and impacts of the UPC contributes to several lines of research. First, a number of studies consider the economic impacts of changes in US retailing, starting in the 1980s (e.g., Foster, Haltiwanger, and Krizan 2006). Within that literature, some authors suggest that bar codes contributed to the emergence of large chains (e.g., Basker, Klimek, and Van 2012; Raff and Schmitt 2016), which in turn stimulated increases in product variety and international trade (Sullivan 1997; Broda and Weinstein 2006; Basker and Van 2010). To our knowledge, this is the first paper to provide evidence directly linking retail technology adoption to product innovation and trade.

Second, there is a small empirical literature on bar codes and scanning. Dunlop and Rivkin (1997) and Dunlop (2001) document the diffusion of UPC registrations across sectors and time. They show that through 1975 nearly two-thirds of registrations were by food and beverage companies but that by 1982 these firms constituted a minority of new registrations. We present new stylized facts including that registration rates were strongly correlated with firm size and varied considerably by industry within the manufacturing sector.

Third, we contribute to the literature on technology diffusion with network effects, as summarized by Farrell and Klemperer (2007). Specifically, we provide reduced-form evidence of positive externalities between the two sides of the UPC platform: bar codes and scanners. Other studies that measure network effects in two-sided platform adoption include Gandal, Kende, and Rob (2000) for compact discs (CDs) and CD players and Gowrisankaran, Rysman, and Park (2010) for digital video discs (DVDs) and DVD players.

Fourth, because UPC adoption is a proxy for broader information technology (IT) investments within retail supply chains, this study fits into a literature on IT and vertical relationships. Many studies in this literature treat vertical scope as endogenous to IT (Brynjolfsson et al. 1994; Hitt 1999; Forman and McElheran 2019), although evidence shows that firms often use external suppliers even when they are vertically integrated (Atalay, Hortaçsu, and Syverson 2014). Fort (2017) shows that IT adoption is associated with supply-chain fragmentation. Rather than asking how UPC adoption influenced the organization of firms or their supply chains, this paper considers how supply chains shaped UPC diffusion and also measures the broader impacts of UPC adoption on product variety and trade.

Finally, we contribute to a literature on the diffusion and economic impacts of industry standards. There are many descriptive accounts of standardization. For example, Levinson (2006) provides a history of the shipping container, and the volume edited by Greenstein and Stango (2007) contains several other case studies. Quantitative studies on the causal impacts of standards adoption are less common. Recent exceptions include the studies by Bernhofen, El-Sahli, and Kneller (2016), who find large increases in bilateral trade between countries that have each installed one or more container-ready ports; Brooks, Gendron-Carrier, and Rua (2018), who link containerization to local economic growth, using the prior depth of the nearest port as an instrument for the decision to containerize; and Gross (2020), who shows that converting 13,000 mi of US railroad track to a standard gauge over a single weekend in 1886 led to a sizable redistribution of traffic away from steamships. This paper describes how the UPC standard was created, provides empirical evidence on its diffusion, and shows how it influenced employment and innovation among early adopters in manufacturing industries.

The balance of the paper proceeds as follows: section II provides general background on the UPC and its diffusion. Section III describes the data sources and our methods for combining them. In section IV, we present our analysis of UPC diffusion, including evidence of network effects. Section V presents estimates of the impact of UPC adoption on employment, revenue, trademarking, and international trade. Section VI concludes.

II. The Universal Product Code

The UPC—originally the Uniform Grocery Product Code (UGPC)—is a system of assigning a unique number to every product.[3] It was initiated, designed, and implemented in the 1970s by food industry participants—manufacturers, wholesalers, and retailers—with no government oversight. Unlike the previous major retail innovation of mechanical cash registers, introduced in the 1880s, bar codes required standardization across the supply chain. The developers of the UPC expected that most benefits would accrue to retailers but significant costs would be borne by suppliers (Brown 1997, 114). Manufacturers were still motivated to participate, at least partly from fear that without an industry standard, each large grocery chain would require its suppliers to adopt a set of proprietary symbols (Brown 1997, xv).

As designed by the Ad Hoc Committee on a Uniform Grocery Product Identification Code in the early 1970s, the bar code consisted of two five-digit numbers. The first five-digit number, a member prefix, was assigned by the Uniform Code Council (UCC) to paying member firms. Prefixes were purchased on a one-time basis at sliding scale rates ranging from a couple hundred dollars to over $10,000 depending on revenue (Brown 1997, 119, 151).[4]

[3] Although we use the acronym UPC for simplicity, the Universal Product Code is officially abbreviated “U.P.C.” because the certification mark on “UPC” is held by the Uniform Plumbing Code.

[4] UPC adopters were not limited to a single registration, and many large firms registered for multiple prefixes. Thus, the registration cost does not appear to have been prohibitively high. In 1990, the number of digits in the prefix increased from five to six (Brown 1997, 191).

The second part of the code was assigned by the firm and could vary by product type, size, color, flavor, and other product characteristics. Computer code associated each prefix with a manufacturer and each suffix with a product and a price.

Registering for a UPC prefix is necessary but not sufficient for placing bar codes on products. It is the latter innovation that enables scanning by retail outlets. Printing the bar code symbol required manufacturers to redesign their product labels to make room for the symbol and in some cases to invest in printing technologies that allow for sufficiently precise bars and minimize smearing. Importantly, our data allow us to determine when a company registered for one (or more) UPC prefixes but not whether, when, or at what intensity it incorporated bar codes into its product labels.

Adding UPC symbols to packaging benefits downstream firms only to the extent that they utilize scanners. At first, checkout scanner adoption proceeded more slowly than the UPC registration process. For example, Brown (1997, 115) reports that by mid-1975, "50 percent (by volume) of the items in a supermarket were source-marked with U.P.C. symbols, and thirty stores were actually scanning at the checkout counter." One year later, an editorial in *UPC Newsletter* noted that there had been just 78 retail scanner installations compared with 4,412 manufacturer UPC registrations (Uniform Product Code Council 1976). One reason for this imbalance was that a single UPC registration—sufficient for a firm with 100,000 individual SKUs—was much cheaper than installing scanners at the checkout.[5]

Basker (2012, fig. 1) shows that scanner adoption began to accelerate around 1981. By 1984, roughly 8% of US grocery stores had installed a scanner at checkout.[6] Around that time, the major general merchandise retailers started using scanners in the back end of stores for inventory management, often in conjunction with early EDI implementations. For example, Kmart reported that in 1981 it implemented back-end scanners whereby "store employees use a wand to scan hardline merchandise on the sales floor and in the stockroom, assuring accurate replacement of goods" (Kmart 1982, 9). From 1982 to 1986, each of Walmart's annual reports makes some reference to investments in UPC-based point-of-sale scanning systems. Abernathy and Volpe (2011) report that Kmart and Walmart required apparel suppliers to place a bar code on every item starting in 1983 and 1987, respectively.

[5] Basker (2012) estimates the cost of an early scanning system for a multilane supermarket at $300,000 in 1982 dollars.

[6] The 8% estimate comes from comparing 10,000 scanner installations with the 121,049 grocery establishments reported in the 1982 Census of Retail Trade (CRT). A series of papers by Levin, Levin, and Meisel (1985, 1987, 1992) and Das, Falaris, and Mulligan (2009) document the dynamics of scanner diffusion across US grocery chains and metropolitan areas. Beck, Grajek, and Wey (2011) study scanner adoption in Europe.

III. Data

To study the diffusion and impacts of the UPC, we construct a panel data set containing information on UPC registrations, employment, and trademarking for approximately 779,300 manufacturing firms over the period 1975–92, comprising 5.1 million firm-year observations. Table 1 reports summary statistics for this panel. On average, the firms in our data employed 72.8 persons and had $14.4 million in annual revenue (in 1992 dollars), though as with most firm-level data sets, the size distribution is highly skewed.[7] There is considerable churn, with around 9.7% of active firms exiting the panel in any given year.

We use two source files to identify UPC registrations: a July 1974 membership list in the Uniform Grocery Product Code Council (Distribution Codes 1974) and updated membership files used by John Dunlop in several papers (including Abernathy et al. 1995 and Dunlop 2001) and by Mobius and Schoenle (2006). There are close to 100,000 registrations through 1992 in the Dunlop file. Figure 1*A* shows the flow of new US registrations per year. After an initial wave of registrations in 1974 and 1975, UPC adoption slowed for several years, before starting a steady climb that lasted through 1992. We also observe some bunching in 1983, consistent with widespread adoption of the UPC by general merchandise suppliers around that time. Figure 1*B* shows the distribution of the size class variable based on reported annual revenue (in millions of dollars) of the registering firm (Zimmerman 1999, app. E). The vast majority of registrants are small firms with annual revenue under $2 million.

We use name and address data in the UPC registration files to match registrants to business establishments in either the Economic Census (1977, 1982, 1987, and 1992) or the Business Register (1975–92). Details of the matching procedure are described in appendix A (apps. A–D are available online).[8] Ultimately, we successfully match between 40% and 50% of UPC registrations to establishments in three sectors: manufacturing, wholesale, and retail. The match rate is around 70% for firms with $2 million or more in annual revenue and around 40% for firms below that threshold.[9]

To create a panel data set, establishments are linked over time using the Longitudinal Business Database (LBD) and aggregated to the firm

[7] We do not report medians, but the Business Dynamics Statistics data indicate that the median-sized manufacturer in 1977 had between 10 and 19 employees. See http://www2.census.gov/ces/bds/firm/bds_f_szsic_release.xlsx.

[8] The Economic Census includes the Census of Manufactures (CM), Census of Wholesale Trade, CRT, and other sector-specific censuses.

[9] Figure A-1 (figs. A-1, C-1, and C-2 are available online) shows the match rate by year and by firm size. A disproportionate share of early adopters consists of relatively large firms. For instance, the share of registrations in the $0–2 million size class increases sharply from 26% in 1972 to 86% in 1978, after which it stabilizes between 85% and 90%. For firms above $2 million in revenue, our match rates are similar to those obtained by Jarmin (1999) for manufacturing plants and Kerr and Fu (2008) for patent filers.

TABLE 1
FIRM SUMMARY STATISTICS

	Mean	Standard Deviation
Employees	72.8	1,540
Revenue	14.4	.592
$\mathbb{I}[\text{Exit}\,\vert\,\text{Alive}_{t-1}]$	.097	.296
UPC adoption: UPC_{it}	.019	.135
Ever UPC	.038	.190
Channel adoption: $\widehat{\text{UPC}}_{it}$	.071	.121
Rival adoption: $\overline{\text{UPC}}_{it}$	.161	.170
Trademark: TM_{it}	.016	.117
Ever TM	.081	.266
Firms[a]	779,300	
Observations[a]	5,112,400	

NOTE.—Observations are firm-years for 1975–92, except for revenue (reported in millions of 1992 dollars, using data from Economic Census years only). UPC_{it} is an indicator for firm i having a UPC registration by year t. "Ever UPC" is an indicator for the firm having a UPC registration at any point during the sample period (1975–92). Channel adoption ($\widehat{\text{UPC}}_{it}$) is the employment-weighted value of UPC_{it} across firms in other industries selling to the same downstream retailers. Rival adoption ($\overline{\text{UPC}}_{it}$) is the employment-weighted value of UPC_{it} across other firms in the same industry. TM_{it} represents the number of TMs that firm i registered in year t. "Ever TM" is an indicator for the firm having one or more TMs during the sample period.

[a] Firm and observation counts are rounded to comply with Census Bureau rules on disclosure avoidance.

level.[10] Firm age is defined as the difference between the current year and the year that the firm identifier first appears.[11] Table 1 shows that 3.8% of the observations belong to a manufacturer that registered for a UPC by 1992. At the firm-year level, the UPC adoption rate is 1.9%, suggesting that adopters held a UPC for about half of the years in which they appear in the data. These numbers understate UPC diffusion because of the highly skewed firm-size distribution and the fact that larger firms were more likely to adopt early, as we show in the next section.

Our analysis of network effects relies on two measures of aggregate UPC adoption to proxy for the installed base of scanners. The first variable is based on UPC adoption by firms in the same four-digit Standard Industrial Classification (SIC) code as the focal firm and is denoted by $\overline{\text{UPC}}_{it}$. The second variable measures UPC adoption by manufacturers in other four-digit SIC codes that sell through the same retail channels as a focal firm and is represented by $\widehat{\text{UPC}}_{it}$. For example, consider a firm in SIC 2033, "Canned fruits and vegetables."[12] For this firm, $\overline{\text{UPC}}_{it}$ measures

[10] The LBD is described in detail in Jarmin and Miranda (2002) and Stinson, White, and Lawrence (2017). Details of the aggregation procedure are described in app. sec. A.2.

[11] The first year is either 1972 (if any of the firm's establishments appear in the 1972 CM) or 1975 and later, because the LBD starts in 1975.

[12] As detailed in app. sec. A.2, firms are classified by their predominant industry. Firms that operate multiple establishments are therefore classified in a single industry despite having some establishments in other industries.

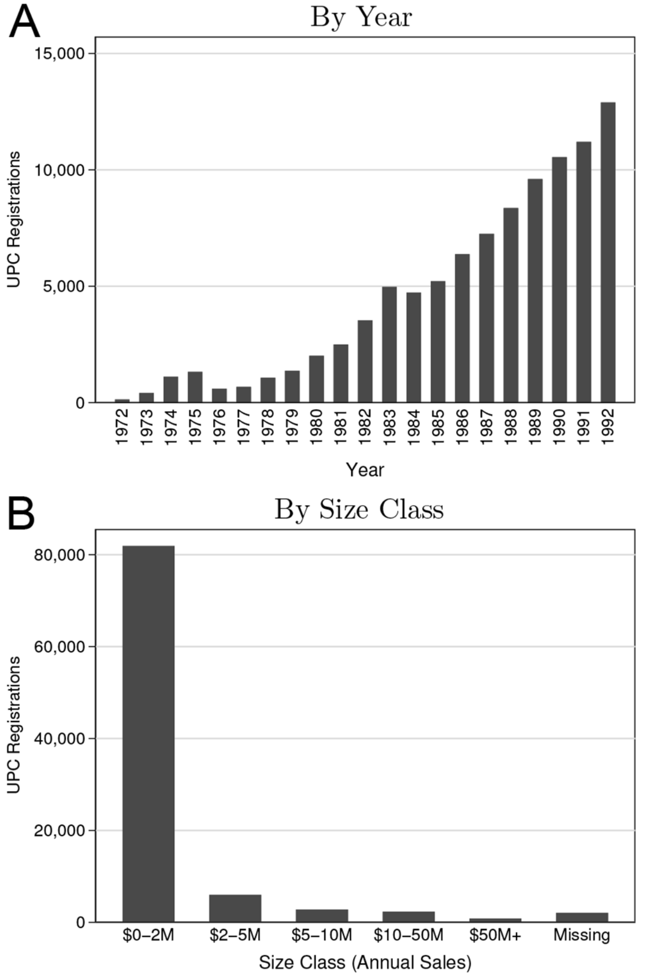

FIG. 1.—New UPC registrations. Source: authors' calculations from UCC data. Firm revenue bins are as provided by the UCC, except for the $50M+ bin, which aggregates three bins.

the employment-weighted UPC adoption rate of other firms in SIC 2033, whereas $\widehat{\mathrm{UPC}}_{it}$ reflects the employment-weighted UPC adoption rate of firms in other industries, such as salad dressing producers, tobacco producers, and magazine publishers, which also sell to grocery stores.

To create $\widehat{\mathrm{UPC}}_{it}$, we rely on data from the 1977 CRT, along with a handmade concordance between four-digit manufacturing SIC codes and "broad-line" product categories in the CRT data (examples of broad lines are food, women's apparel, and furniture). This concordance allows us to compute two sets of weights: u_{rm} measures the share of retail industry r's

1977 revenue derived from manufacturing industry m's products, and s_{mr} measures the share of manufacturing industry m's 1977 sales through retail channel r.[13] For each firm i in manufacturing industry j, we then compute

$$\widehat{\text{UPC}}_{it} = \sum_{r \in R} s_{jr} \left[\sum_{m \in \{M \setminus j\}} u_{rm} \overline{\text{UPC}}_{mt} \right], \tag{1}$$

where R represents the set of all four-digit retail SIC codes, $\{M \setminus j\}$ represents the set of all manufacturing industries except for j, and $\overline{\text{UPC}}_{mt}$ represents the employment-weighted industry average UPC adoption for manufacturing industry m in year t. Table 1 shows that $\overline{\text{UPC}}_{it}$ averages 16.1% and $\widehat{\text{UPC}}_{it}$ averages 7.1% across all manufacturing firm-years in our panel. These numbers are substantially higher than the firm-level UPC adoption rate because of the employment weights and the fact that large firms adopted the UPC earlier.

To study the link between UPC adoption and product innovation, we employ data on US TM applications from the USPTO Trademark Case Files Dataset (Graham et al. 2013).[14] A TM is a "word, phrase, symbol, design, color, smell, sound, or combination thereof" that identifies products sold by a particular party (15 U.S.C. § 1127). Although TMs need not be registered, federal registration in the United States provides prima facie evidence of ownership, affords nationwide protection, and is required for enforcement in federal court. Millot (2009) reviews the empirical literature on TMs and argues that they are a useful indicator of product and marketing innovation. Our proxy for product innovation is an indicator that a firm applied for at least one new TM that eventually became a registered TM.[15] Table 1 shows that 8.1% of the observations in our panel belong to a firm that applied for at least one new TM and that the annual probability of filing a new TM was 1.6%, which together imply that trademarking firms registered TMs on average once every 5 years.

Finally, we create an industry-year panel with measures of UPC adoption and international trade. Specifically, we supplement the 1987 SIC version of the National Bureau of Economic Research–Center for Economic Studies (NBER-CES) Manufacturing Industry Database with industry-level UPC

[13] Appendix sec. A.3 provides a complete description of how $\overline{\text{UPC}}_{it}$ and $\widehat{\text{UPC}}_{it}$ are created. The data and code used to produce the weights u_{rm} and s_{mr} are available at http://people.bu.edu/tsimcoe/data.html.

[14] The data on TMs are merged with the Business Register via the matching procedure described in Dinlersoz et al. (2021), and we are indebted to these authors for making their match available to us.

[15] This restriction is important because, starting in 1989, firms could file "intent to use" applications for TMs that were never actually used, and we observe a large increase in applications around that time. Registration indicates that the TM was actually used in commerce. Also, to avoid double counting TMs that change hands, we restrict our counts to the original applicant.

adoption, calculated from the micro data, and merge it with data on US imports and exports by four-digit SIC, based on data collected by Feenstra (1996) and concordances from Schott (2008, 2012). After combining a small number of industries that have no imports (or import only from Canada) with closely related industries (to avoid zero cells when we take logs), this yields a strongly balanced panel of 422 manufacturing industries for the years 1975–92.[16]

IV. Diffusion

A. *Firm Size and Industry*

We start by partitioning all manufacturing firms in each Economic Census year by revenue quartile and calculating the share of firms in each quartile that have registered for a UPC by that year. The registration rates are shown in figure 2. Among firms in the largest quartile, approximately 2% registered for a UPC by 1977 and nearly 10% registered by 1992. Smaller firms have lower registration rates; less than 2% of firms in the third and fourth quartiles registered for a UPC by 1992.

Our data also reveal differences in UPC adoption across manufacturing industries. The UGPC was initially a grocery product code, intended for use by food manufacturers, retailers, and wholesalers. After a slow start, by 1980 Harmon and Adams (1984, 7) report that more than 90% of grocery products displayed bar codes. General merchandise stores soon "noted the benefits of uniform product coding . . . [and] began to demand that their vendors adopt the U.P.C." (Dunlop and Rivkin 1997, 5). Figure 3 reinforces the idea that the UPC was widely adopted within the grocery supply chain before spreading to general merchandise. Each panel plots UPC adopters' share of firms and employment within a selected manufacturing industry. All panels are on the same scale, but the firm share and employment share use different axes.

The share of firms with UPC registrations in food manufacturing (top left panel) is about 5% in 1975 and increases to about 20% by 1992. The employment share of UPC registrants, however, remains fairly stable at 60%, reflecting the fact that large firms registered early and later registrants are small.[17] In chemical production, which includes pharmaceuticals, adoption by large firms occurs early but both the employment share

[16] Documentation and summary statistics for the NBER-CES Manufacturing Industry Database productivity data are available at http://www.nber.org/nberces, and US imports and exports by 1987 SIC are available at https://sompks4.github.io/sub_data.html.

[17] Food manufacturers include both intermediate- and final-goods manufacturers. We expect the registrations to be disproportionately concentrated among final-goods manufacturers, so these rates may be underestimates of the registration rates among final-goods producers.

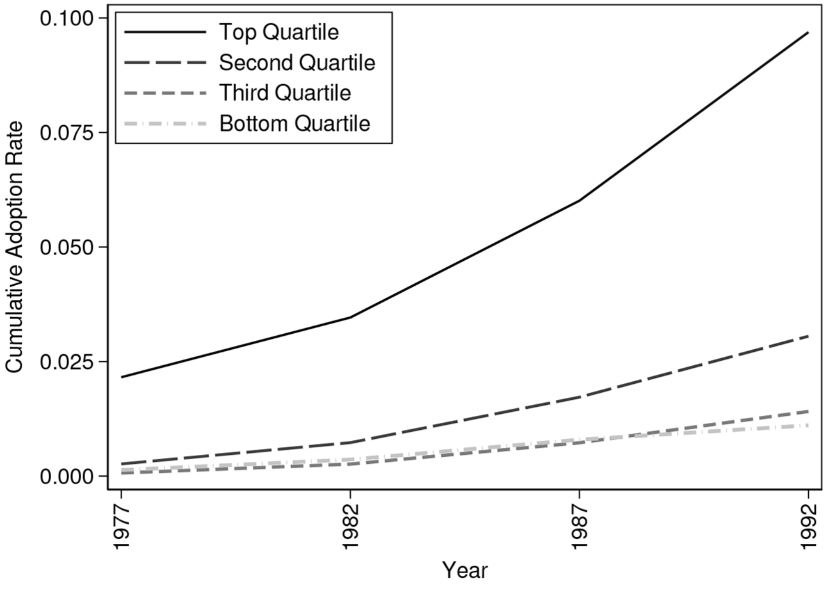

FIG. 2.—UPC adoption by firm revenue. Source: authors' calculations from matched UCC and Census Bureau data. The figure shows the share of manufacturers in each Economic Census year and each revenue quartile that have adopted the UPC by that year.

and the firm share of adopters increase steadily over time. Both food and chemical manufacturers are likely to sell through the grocery supply chain. The other four industries in figure 3 (apparel, electronics, furniture, and textile manufacturing) mostly supply their respective specialty retailers, as well as general merchandise retailers. For these four industries, growth in UPC adoption begins in the early 1980s and takes off more slowly, though employment growth exceeds firm growth because here, too, larger firms adopt earlier.

B. *Network Effects*

The UPC is a classic case study for two-sided network effects. The basic argument is that upstream manufacturers had no incentive to make the investments—up to $10,000 for a UPC registration, plus the cost of redesigning product labels and (possibly) printing technology necessary to print precise bar codes that would not smear—until a critical mass of downstream firms had the means to take advantage of these investments. Downstream firms, meanwhile, had little incentive to make their own investments in scanners, computer hardware and software, and employee training until a critical mass of upstream firms printed bar codes on their products. Overcoming this "chicken and egg" problem was the goal of

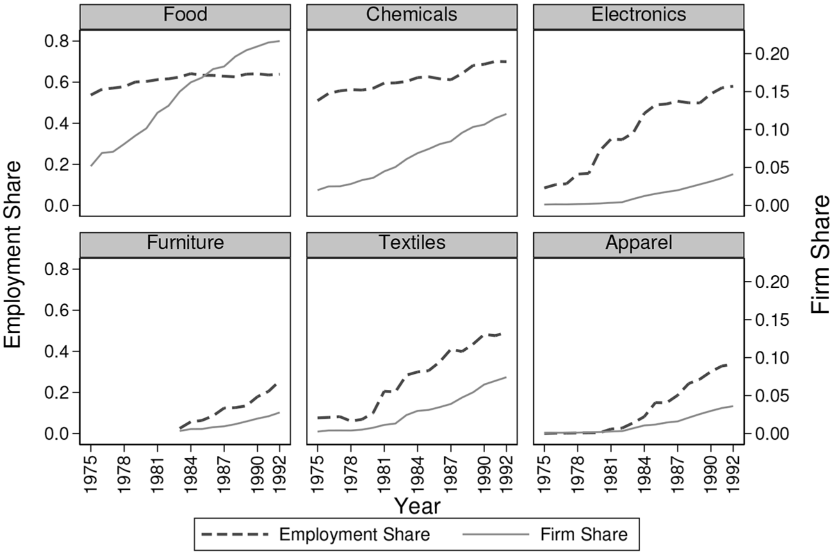

FIG. 3.—UPC adoption for selected two-digit SIC manufacturing industries. Source: authors' calculations from matched UCC and Census Bureau data. The figure shows the share of firms and employment in selected two-digit manufacturing industries that have adopted the UPC by that year.

the UGPC Council (UGPCC). The UGPCC believed that the critical mass on the manufacturing side of the market was 75% of grocery product labels with a bar code and on the retail side was 8,000 supermarkets with scanners installed (Dunlop and Rivkin 1997, 28).

With comprehensive data on UPC adoption, scanner adoption, and supply-chain links, one could estimate network effects via a system of equations,

$$\Delta \mathrm{UPC}_{it} = \alpha^u + \beta^u \mathrm{Scanner}_{J(i),t} + \varepsilon^u_{it}, \tag{2}$$

$$\Delta \mathrm{Scanner}_{jt} = \alpha^s + \beta^s \mathrm{UPC}_{I(j),t} + \varepsilon^s_{jt}, \tag{3}$$

where the outcomes $\Delta\mathrm{UPC}_{it}$ and $\Delta\mathrm{Scanner}_{jt}$ are binary variables indicating that manufacturer i registered for a UPC prefix or retailer j installed a scanner in year t and the explanatory variables $\mathrm{Scanner}_{J(i),t}$ and $\mathrm{UPC}_{I(j),t}$ measure the stock of scanning retailers $J(i)$ or bar-coding manufacturers $I(j)$ within the focal firm's supply chain.[18] Indirect network effects imply positive values for both β^s and β^u.

[18] In a fully structural dynamic model, the key explanatory variables would likely be written as $\mathbb{E}_t(\mathrm{Scanner}_{J(i),t+1})$ and $\mathbb{E}_t(\mathrm{UPC}_{I(j),t+1})$, to denote the expected future stock of bar codes or scanners. We adopt a linear specification and ignore questions of how to model expectations of future adoption for simplicity of exposition.

Estimating this model directly is not possible with our data. In particular, we have only coarse industry-level information about supply chains and in most cases no data on scanner adoption.[19] To derive a feasible reduced-form specification, we integrate equation (3) over retailers and time periods to obtain

$$\text{Scanner}_{J(i),t} = \sum_{\tau \leq t} \sum_{k \in J(i,\tau)} \alpha^s + \beta^s \text{UPC}_{I(k),\tau} + \varepsilon^s_{k\tau}, \tag{4}$$

where $J(i, \tau)$ represents the set of retailers supplied by manufacturer i that have not adopted scanning by τ. The main message of equation (4) is that the stock of scanning retailers in manufacturer i's supply chain can be expressed as a weighted average of UPC adoption by other manufacturers that supply those same retailers. Substituting equation (4) into equation (2) suggests that we can estimate $\beta^s \times \beta^u$ using variation in UPC adoption by other manufacturers that sell through the same channels as manufacturer i. This reduced-form parameter should be positive when there are indirect network effects.

In practice, we replace $\text{Scanner}_{J(i),t}$ in equation (2) with either $\widehat{\text{UPC}}_{it}$ or $\overline{\text{UPC}}_{it}$ to obtain the reduced-form specification

$$\Delta\text{UPC}_{it} = \lambda_{at} + \beta\widehat{\text{UPC}}_{it} + X_{it}\theta + \varepsilon_{it}, \tag{5}$$

where λ_{at} represents a full set of firm-age by calendar-year fixed effects and X_{it} represents exogenous controls.[20] Each firm is retained in the data only until the year when it registers, so that β can be interpreted as the change in the hazard of UPC adoption if all other manufacturers selling through the same retail channels switched from being nonadopters to adopters.[21]

Manski (1993) discusses identification of models such as equation (5), where an individual choice is regressed on a group average of the same outcome. We interpret β as what Manski calls a correlated effect: manufacturers with similar values of $\widehat{\text{UPC}}_{it}$ (or $\overline{\text{UPC}}_{it}$) make correlated choices

[19] Appendix sec. B.1 provides an analysis of grocery store scanner adoption between 1974 and 1984, using data from Basker (2012, 2015). Although this exercise lends some plausibility to the indirect network effects interpretation of our main results, we cannot estimate a two-sided model for the larger data set because we lack information on scanner adoption outside the grocery industry and for later years.

[20] In app. D, we provide a continuous-time model of UPC and scanner adoption by firms in an arbitrary number of upstream and downstream industries. This model yields a linear system of first-order differential equations, analogous to eqq. (2) and (3), whose solution is eq. (5). The model also provides a microfoundation for the formula in eq. (1) that define $\widehat{\text{UPC}}_{it}$.

[21] Jenkins (1995) discusses estimation of discrete-time duration models using "panel" data with one observation per unit per period until exit (here, UPC registration) and shows that logit models reproduce the likelihood for a proportional hazard specification. We estimate the analogous ordinary least squares (OLS) regression.

because they face a similar institutional environment—specifically, downstream customers that have installed scanners. The alternative interpretation, which Manski calls an endogenous effect, is that UPC adoption by other manufacturers has a direct causal impact on the decisions of a focal firm. Empirical models of indirect network effects typically rule out endogenous effects, which are also called direct network effects or "same side" externalities, to achieve identification (Rysman 2019). This is a plausible assumption in our setting, where spillovers among upstream UPC adopters are likely to be minimal in the absence of downstream scanning.

Table 2 reports estimates based on equation (5). Standard errors are clustered by four-digit firm SIC, and all models include controls for lagged firm employment and vertical integration (i.e., an indicator for firms with one or more wholesale or retail establishments). Columns 1 and 2 present estimates from a pure correlated-effects model, which implicitly assumes no unobserved industry-level heterogeneity. The network effects parameter is positive and statistically significant for both channel ($\widehat{\mathrm{UPC}}_{it}$) and rival ($\overline{\mathrm{UPC}}_{it}$) adoption. To provide a sense of the economic magnitudes, note that a 1 standard deviation change in $\widehat{\mathrm{UPC}}_{it}$ (as reported in table 1) doubles the baseline hazard of UPC adoption (from 0.34% to 0.67% per year), and a 1 standard deviation change in $\overline{\mathrm{UPC}}_{it}$ increases the baseline hazard by approximately 130%.

One concern with the initial estimates in table 2 is that correlated industry-level unobservables, such as a lower average cost of UPC adoption, might be mistaken for network effects. We find the indirect network

TABLE 2
UPC Adoption Hazard Regressions

Spillover	Channel (1)	Industry (2)	Channel (3)	Industry (4)	ZIP (5)
Channel: $\widehat{\mathrm{UPC}}_{it}$	.0276***		.0196***		
	(.0049)		(.0045)		
Rival: $\overline{\mathrm{UPC}}_{it}$		.0261***		.0125***	−.0004
		(.0023)		(.0015)	(.0004)
SIC/ZIP fixed effects			✓	✓	✓
Industry value added			✓	✓	
Mean outcome			.0034		
Observations[a]			5,033,100		

Note.—Outcome is UPC adoption. Firms remain in the sample until their first UPC adoption. Channel adoption ($\widehat{\mathrm{UPC}}_{it}$) is the employment-weighted value of UPC_{it} across firms in other industries selling to the same downstream retailers. Rival adoption ($\overline{\mathrm{UPC}}_{it}$) is the employment-weighted value of UPC_{it} across other firms in the same industry. All regressions control for firm-age × year effects, $\ln(\mathrm{Employment}_{t-1})$, and a vertical integration indicator. Robust standard errors clustered by firm SIC (ZIP) are given in parentheses.

[a] An observation is a firm-year. Observation counts are rounded to comply with Census Bureau rules on disclosure avoidance.

*** $p < .01$.

effects interpretation to be more plausible because the costs of UPC adoption do not seem to have a large industry-specific component. It is also reassuring that the coefficients on $\widehat{\mathrm{UPC}}_{it}$ and $\overline{\mathrm{UPC}}_{it}$ are quite similar, since the former measure excludes any variation produced by UPC adoption in the same four-digit manufacturing industry as a focal firm. Nevertheless, to address the possibility of industry-level omitted variables, such as a coordinated effort to start UPC and scanner adoption in a particular industry, columns 3 and 4 in table 2 present results from a specification that controls for industry fixed effects and time-varying log industry value added. For both channel and rival adoption, the indirect network effects parameter remains positive and statistically significant. Although point estimates decline by 30%–50% relative to columns 1 and 2, in the case of $\widehat{\mathrm{UPC}}_{it}$ the confidence intervals include a wide overlap range.[22]

We interpret the estimates in table 2 as evidence of indirect network effects. An alternative interpretation is that firms simply imitate other UPC adopters. These two mechanisms cannot be distinguished if imitation takes place primarily within industries or supply chains. If there is a geographic component to imitation, however, we can attempt to falsify the "no endogenous effects" assumption that underpins the network effects interpretation. In column 5 of table 2, we redefine $\overline{\mathrm{UPC}}_{it}$ as the employment-weighted share of UPC adoption in a firm's three-digit ZIP code (instead of its four-digit industry) and reestimate equation (5).[23] The results show that geographic spillovers in manufacturer UPC adoption are negligible and thereby lend support to our preferred interpretation that manufacturers are not simply imitating one another.

V. Impacts of UPC Adoption

This section estimates the impacts of UPC adoption on several outcomes. At the firm level, we analyze employment, revenue, and product innovation (as measured by new TMs).[24] At the industry level, we examine the relationship between UPC adoption and international trade.

[22] One concern with the inclusion of SIC fixed effects is that both $\widehat{\mathrm{UPC}}_{it}$ and $\overline{\mathrm{UPC}}_{it}$, which aggregate previous UPC adoption decisions, implicitly contain lagged outcomes, leading to a violation of strict exogeneity. The resulting bias is likely to be small, however, because the time (firm-year) dimension of our panel is large. In particular, Nickell (1981) shows that under the assumption of sequential exogeneity, the bias of the within estimator is inversely proportional to T. We cluster at the four-digit SIC level, which implies a panel of around 600 manufacturing industries, each containing an average of $T = 8{,}500$ observations.

[23] Colocation is associated with increased interfirm trade (e.g., Hillberry and Hummels 2008), which might create the false appearance of geographic spillovers in UPC adoption. The potential bias works against our falsification test, however, and we expect it to be small (relative to any true geographic spillover) because even small locations host a wide range of establishments that are unlikely to trade with one another.

[24] In app. C, we present parallel results for 866,500 wholesalers over the same time period.

A. *Employment and Revenue*

1. Difference-in-Differences Estimates

To estimate the impacts of UPC adoption, we use the following difference-in-differences specification:

$$Y_{it} = \alpha_i + \gamma_{mt} + \lambda_{at} + \beta \mathrm{UPC}_{it} + \varepsilon_{it}, \tag{6}$$

where Y_{it} represents firm i's logged employment or revenue or is an indicator for TM registration status in year t, α_i represents a firm fixed effect, γ_{mt} represents an industry-year effect linked to the predominant industry of firm i, λ_{at} represents a firm-age by calendar year effect, and UPC_{it} is an indicator that turns on if and only if firm i registered for a UPC by year t. The industry-year fixed effects provide a flexible specification of the outcome's dynamics in each four-digit SIC manufacturing industry. The age-year fixed effects capture many unobservable factors, including the fact that firms tend to grow as they age and that young and old businesses react differently to business cycle shocks (Fort et al. 2013; Haltiwanger, Jarmin, and Miranda 2013). Standard errors are clustered by four-digit firm SIC to allow for arbitrary autocorrelation in the error term ε_{it} as well as arbitrary correlation across firms in the same industry.

We construct two different estimation samples for this analysis. The first keeps all firms that did not adopt UPC before 1992 as controls, and the second matches adopters to nonadopters on the basis of size and employment growth.[25] The one-to-one matched sample is constructed as follows. First, we identify the pool of potential matches for firm i, which registered for a UPC in year t, as firms that had nonzero employment in year t and did not register for a UPC by 1992. If firm i is observed for the first time in the year of registration, we randomly assign one firm of the same vintage in the same year as a match. If firm i is observed for the first time 1 year before registration, we assign a match using its age and vintage and year $(t - 1)$ employment level.[26] For firms aged 2–5 at registration, we match using vintage, year $(t - 1)$ employment, and log employment growth between year of birth and year $(t - 1)$.[27] Finally, we match firms aged 6 and over at the time of registration to other firms that are at least 6 years old in year t by year $(t - 1)$ employment and by log employment growth between year $(t - 5)$ and year $(t - 1)$. Registrants that do

[25] Employment and revenue are both proxies for firm size. We do not match on revenue or revenue growth because revenue is available only in 5-year intervals from the Economic Census. Instead, we report estimates from the employment-matched sample using total revenue as the outcome variable.

[26] We bin employment in 50 bins per year, each with 2% of the firms. We drop any bins whose maximum size exceeds 110% of their minimum size to ensure that employment at matched control observations is within 10% of employment at treated observations.

[27] We find the closest match on employment growth, with the restriction that the two firms' employment growth cannot differ by more than 0.5%.

not have a matched control firm are dropped. Matching is done without replacement.

We do not restrict matches to have the same manufacturing industry SIC for several reasons. First, if UPC adoption is driven by the downstream demand for bar codes, which varies more between industries than within them, matching across industries should reduce concerns about selection on firm-level unobservables. Intuitively, the experiment we would like to run randomly assigns manufacturing firms to supply chains with and without downstream scanners. Between-industry matching brings us closer to this notional experiment, whereas within-industry matching raises questions about self-selection, given that adopters and nonadopters in the same industry are exposed to similar supply chains. Second, contamination is a concern with intraindustry matching: controls may be affected by their competitors' adoption of the UPC. Third, as a practical matter, restricting to the same four-digit industry reduces the number of possible matches for each treated observation and would therefore decrease the number and quality of the matches.

In the matched-sample analysis, counterfactual outcomes for UPC adopters are estimated by actual outcomes at similarly sized nonadopters that exhibit similar preadoption trends over the same time period. To account for staggered adoption, the matched-sample regressions also include a postadoption indicator, Post_{it}, which turns on for both adopters and their matched control firms in all years following the treated firm's initial UPC registration (or equivalently, UPC_{it} equals Post_{it} multiplied by a time-invariant treatment indicator). We interpret the matched-sample estimates of β as an average treatment effect for treated firms.

Table 3 reports coefficient estimates based on equation (6). The coefficient on UPC adoption is positive and statistically significant in all specifications, and the magnitude of the estimates is quite similar for the employment and revenue outcomes. The baseline OLS estimates imply a 16% increase in employment and a 20% increase in revenue following UPC adoption, whereas the matched-sample estimates suggest a 13% increase in employment and a 10% increase in revenue.[28]

The similar difference-in-differences estimates for revenue and employment suggest that UPC adoption influenced firm size more than productivity or the labor share. Indeed, if we regress the log of revenue per employee on UPC adoption, we find a 3.7% increase in the full sample and a 3% decline in the matched sample, which is very similar to the difference

[28] One potential concern with this specification is that survival rates could differ for adopters and nonadopters. We have estimated the matched-sample difference-in-differences regressions on a balanced sample that drops both the adopter and its matched control when either firm exits the sample, and we have confirmed that this produces qualitatively similar estimates. In app. sec. B.2, we report hazard models showing that UPC adoption is positively correlated with survival.

TABLE 3

EFFECT OF UPC ADOPTION ON FIRM OUTCOMES: DIFFERENCE-IN-DIFFERENCES REGRESSIONS

	EMPLOYMENT		REVENUE		TMs	
OUTCOME SAMPLE	Full (1)	Matched (2)	Full (3)	Matched (4)	Full (5)	Matched (6)
UPC_{it}	.155***	.130***	.204***	.103***	.044***	.045***
	(.007)	(.014)	(.011)	(.022)	(.003)	(.003)
Observations[a]	5,112,400	221,600	1,113,000	44,000	5,112,400	331,000

NOTE.—The table shows difference-in-differences regressions of UPC adoption on firm outcomes. Employment and revenue outcomes are logged. TM outcome is an indicator for any current-year trademarking. All regressions include firm, four-digit SIC × year, and firm-age × year fixed effects. Matched-sample regressions also include a common postadoption indicator for both treatment and control firms. Robust standard errors clustered by four-digit firm SIC are given in parentheses.

[a] An observation is a firm-year. Observation counts are rounded to comply with Census Bureau rules on disclosure avoidance.

*** $p < .01$.

between the revenue and employment coefficients in table 3. In appendix section B.3, we report estimates from an establishment-level version of equation (6) for establishments in the CM and the Annual Survey of Manufactures, using revenue-based total factor productivity (TFP) from Foster, Grim, and Haltiwanger (2016) as the outcome. We find no evidence of a relationship between UPC adoption and manufacturing TFP—the coefficient on UPC adoption is uniformly small and statistically insignificant. Although the absence of a measurable productivity increase might be surprising, Brynjolfsson and Hitt (2000) note that the productivity impacts of IT adoption are often linked to complementary organizational change. A null result is also consistent with the idea that even though upstream adoption of UPC is a necessary condition for bar coding to work, the majority of productivity gains accrued to downstream retailers that invested in scanners and other complementary technology.[29] Indeed, Basker (2012) estimates that labor productivity in grocery stores increased by 4.5% in the initial years following a scanner installation.

2. Event Study

Even with matching, it is hard to say to what extent the regressions in table 3 estimate a selection effect as opposed to a causal effect of UPC adoption. To get a better handle on this question, we estimate a series of event-study regressions using employment as the outcome variable.[30] Our main specification is

$$\ln(\text{Employment}_{it}) = \alpha_i + \gamma_{mt} + \lambda_{at} + \sum_{\tau=-6}^{16} (\delta_\tau + \beta_\tau \text{UPC}_i) + \varepsilon_{it}, \quad (7)$$

where α_i, γ_{mt}, and λ_{at} are defined as above, δ_τ is a vector of indicators that turn on for each adopter-matched control pair if the adopter registered for a UPC in year $(t + \tau)$, and β_τ measures a treatment effect at τ years before or after adoption.[31] We use a single indicator for $\tau \leq -6$ and normalize $\delta_{-1} = \beta_{-1} = 0$. To ensure that we do not include future adopters in the control group, we restrict this regression to observations in 1986 and previous years.

Figure 4 plots the event-study coefficients, β_τ, for the matched sample.[32] The connected dots correspond to point estimates, and the error bars are upper and lower 95% confidence limits. By construction, relative

[29] Because our regressions use revenue-based TFP, it is also possible that manufacturers did experience gains in physical TFP that were offset by an increase in downstream bargaining power leading to lower markups.

[30] It is not possible to provide event-study estimates for the revenue outcome, because revenue is available only in 5-year intervals.

[31] The coefficients represented by δ_τ capture common trends in the treatment and control firms' employment before and after adoption of the UPC by the treatment firms.

[32] All event-study figures omit β_{11} through β_{16}, which tend to be imprecisely estimated because of small cells, raising disclosure concerns.

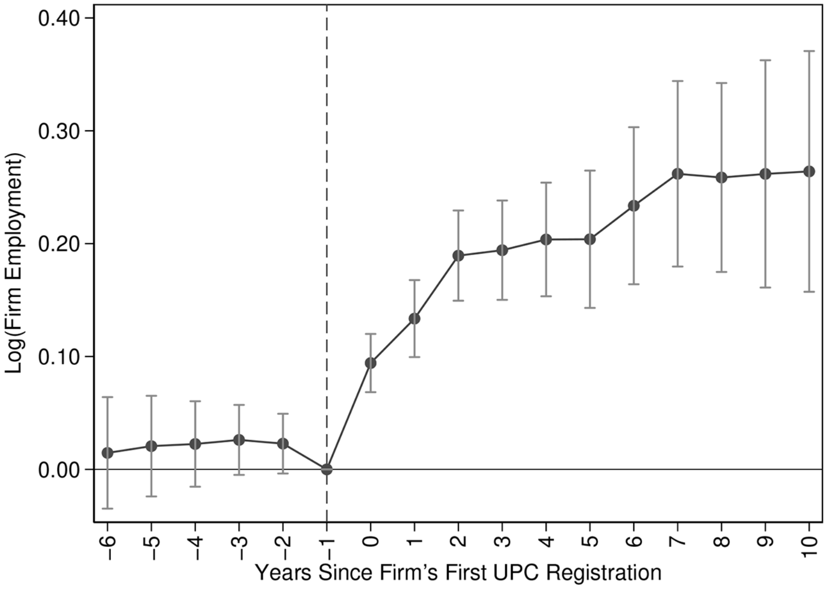

FIG. 4.—Matched-sample event study: employment. Coefficient estimates and 95% confidence intervals are from an event-study regression of UPC adoption on log firm employment. Control firms are a one-to-one match randomly drawn from all firms that do not adopt UPC before 1992, where matching is based on firm age, employment in the year before UPC adoption, and employment growth over the preceding 5 years (without matching on industry). Regression controls include firm, firm-age × year, and industry × year fixed effects, and a common set of pre- and postadoption indicators for both treatment and control firms. See equation (7) in the main text.

employment of adopters and nonadopters between $(t-5)$ and $(t-1)$ is nearly identical and statistically indistinguishable. Following adoption, the treated and control firms clearly diverge: employment increases by about 10% in the year of adoption and then by another 10% over the next 2 years. The abrupt increase in relative employment in the year of UPC adoption is a striking result. The discrete jump suggests to us that manufacturers adopted the UPC specifically to integrate with retail supply chains. This does not mean that UPC adoption caused retail orders to arrive—it seems equally likely that demand shocks caused manufacturers to adopt the UPC. Nevertheless, the sudden increase in employment suggests that UPC adoption was a necessary condition for achieving scale through partnering with larger downstream firms and not merely a proxy for adopting UPC-related technologies and business practices, which would produce more gradual short-run employment growth. Although the confidence intervals increase over time, the point estimates imply that growth continues at least 5–7 years after UPC adoption. This gradual increase in employment (relative to the counterfactual) in later years is consistent with the idea that UPC registration is correlated with downstream scanner adoption, along with a broader set of technological and organizational changes linked to supply-chain automation.

Figure 5 provides two points of comparison that assist in the interpretation of the matched-sample event study. First, figure 5*A* shows event-study coefficients for the full sample.[33] Consistent with the results in table 3, we observe a strong selection effect: in the years before registration, soon-to-adopt firms grow faster than controls. This raises a concern that UPC adoption is correlated with some combination of unobserved managerial ability and opportunity. In principle, we have addressed this concern by matching on firm growth and by including both firm and industry-year fixed effects in equation (7). Comparing figures 4 and 5*A* also clarifies the role of the control firms in our matched-sample analysis. In particular, the different pattern of postadoption coefficients in those two figures implies that the matched controls exhibit mean reversion (i.e., lower than industry average growth rates) after adoption, whereas the UPC adopters do not. The absence of any measurable impact of UPC adoption on TFP also suggests that there is little selection by productivity. Nevertheless, it would be reassuring to see that fast-growing nonadopters in the same industries as UPC adopters do not experience any "UPC adoption" effect. Figure 5*B* presents results from that type of placebo test.

To construct the sample used in figure 5*B*, we first match each UPC adopter to a single nonadopter in the same two-digit SIC, using the procedure described above to ensure that both firms have similar preadoption employment levels and growth trends.[34] We then discard the UPC adopters and treat the remaining sample of matched controls as if they had adopted UPC in the same year as their discarded twins. Finally, we match each firm in this placebo-adopter sample to its own control (in this case allowing for between-industry matching, as we do for the matched sample) and reestimate the event-study model of equation (7). The coefficients graphed in figure 5*B* show that nonadopters from the same broad industries as the UPC adopters, having similar preadoption size and growth trends, do not exhibit any meaningful "treatment" effect. This lends additional confidence to our preferred interpretation of the matched-sample results: a causal impact of joining scanner-enabled supply chains.

3. Network Effects Revisited

To provide more evidence on the role of network effects, we can extend the baseline difference-in-differences model to ask whether the impact

[33] In the regression that produced this figure, we omit the δ_τ coefficients because "years to adoption" τ is not defined for control observations in the absence of a matching procedure.

[34] We match firms at the two-digit SIC level because, as noted above, matching within four-digit industries dramatically lowers either the number or the quality of available matches.

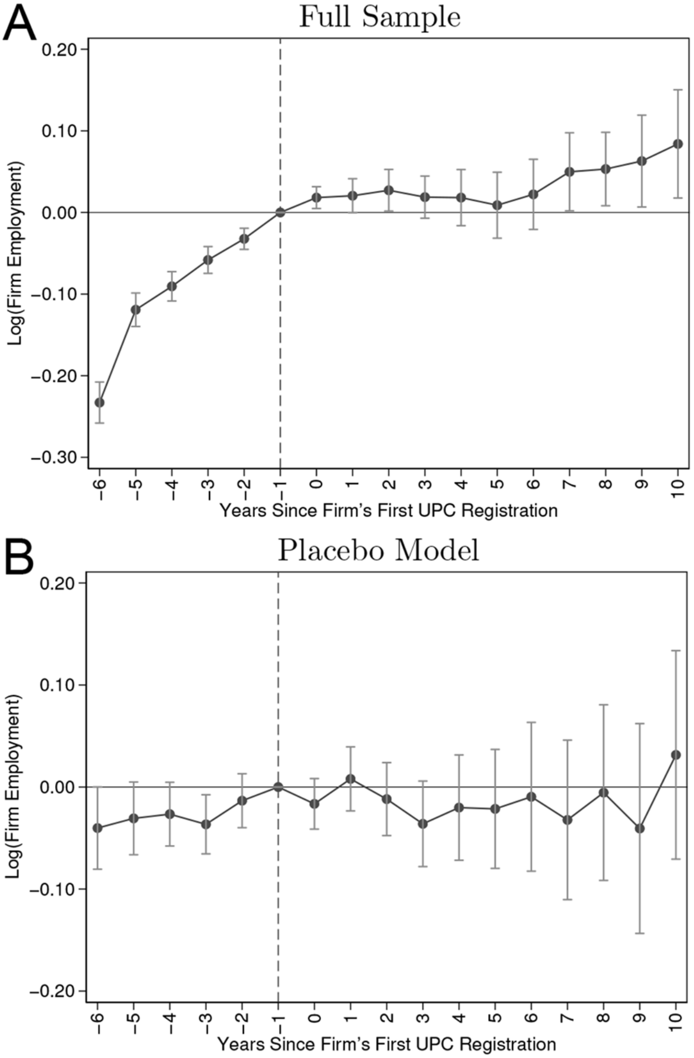

FIG. 5.—Full sample and placebo event studies: employment. Coefficient estimates and 95% confidence intervals are from full-sample and placebo event-study regressions of UPC adoption on log firm employment. The placebo regression uses within-industry matched controls as the placebo treatment group and across-industry matched controls as the controls. Regression controls include firm, firm-age × year, and industry × year fixed effects. The placebo regression also includes a common set of pre- and postadoption indicators for both treatment and control firms.

of UPC adoption on employment and revenue increases with downstream scanner adoption. As in the diffusion analysis, $\widehat{\mathrm{UPC}}_{it}$ and $\overline{\mathrm{UPC}}_{it}$ serve as our proxies for downstream scanner adoption. To implement a test for network effects, we interact one of these proxies with an indicator for focal-firm adoption and add it to the difference-in-differences specification in equation (6). Specifically, we estimate

$$\ln(Y_{it}) = \alpha_i + \gamma_{mt} + \lambda_{at} + \mathrm{UPC}_{it}\left(\beta + \delta\widehat{\mathrm{UPC}}_{it}\right) + \mathrm{Post}_{it}\left(\theta + \omega\widehat{\mathrm{UPC}}_{it}\right) + \varepsilon_{it}, \tag{8}$$

where Y represents either employment or revenue. In this specification, the main effect of $\widehat{\mathrm{UPC}}_{it}$ is absorbed by the industry-year fixed effects.[35] All of our results are based on the matched sample.

Table 4 reports estimates of the direct effect of adoption, β, and the interaction term, δ, for both proxies for scanner adoption. The main effect of UPC adoption, or equivalently the impact of UPC adoption for the first adopter in an industry, is reported in the first row of the table. This coefficient estimate is positive and statistically significant in three of the four models and indicates either a 9%–10% increase in employment or a 5%–7% increase in revenue.

The interaction term, which we interpret as a measure of network effects, is positive and statistically significant across all models. One way to interpret the economic significance of δ is to note that a 1 standard deviation increase in $\widehat{\mathrm{UPC}}_{it}$ raises the predicted marginal effect of UPC adoption from 10% to 12% for employment and from 7% to 10% for revenue.

In this model, we interpret both rival and channel UPC adoption as proxies for downstream scanner adoption.[36] Under that interpretation, our results show that scanner adoption by downstream customers amplifies the impact of UPC adoption on manufacturing firm size. Basker (2012) provides a complementary result for the retail side of the UPC platform: during a period when bar coding variable-weight products (such as fresh produce) was relatively rare, grocery stores that sold more packaged goods realized greater labor productivity gains from scanner adoption.

B. Trademarks

Several scholars have suggested that as UPCs lowered the cost of tracking and managing inventory, retailers became willing to stock a greater variety of products, which in turn increased the incentive for manufacturers to experiment with new product varieties. For instance, Dunlop (2001, 20) writes, “The diffusion throughout the Food and Beverage sector has been steady with associated product proliferation, much larger stores and the

[35] For regressions that use $\overline{\mathrm{UPC}}_{it}$ to proxy for scanning, the main effect is not precisely collinear with the industry-year dummies because the focal firm is omitted from the “industry average.” In practice, we include a main effect for $\widehat{\mathrm{UPC}}_{it}$ in the regressions reported below.

[36] To check whether the interaction terms in table 4 might be picking up treatment heterogeneity by firm size, given that larger firms tended to adopt earlier, when $\widehat{\mathrm{UPC}}_{it}$ was smaller, we estimated a model that allowed the effect of UPC adoption on employment to vary by firm-size quartile. In this model, we found no clear relationship between firm size and the size of the coefficient on UPC_{it}.

TABLE 4
Network Effect of UPC Adoption on Firm Outcomes

	Employment		Revenue	
UPC_{it}	.100***	.092***	.073***	.045
	(.018)	(.022)	(.027)	(.040)
$\text{UPC}_{it} \cdot \widehat{\text{UPC}}_{it}$	.294***		.279**	
	(.087)		(.138)	
$\text{UPC}_{it} \cdot \overline{\text{UPC}}_{it}$		.175***		.262**
		(.063)		(.118)
Observations[a]	221,600	221,600	44,000	44,000

Note.—The table shows difference-in-differences regressions of heterogeneous effects of UPC adoption. Outcomes are logged. Channel adoption ($\widehat{\text{UPC}}_{it}$) is the employment-weighted value of UPC_{it} across firms in other industries selling to the same downstream retailers. Rival adoption ($\overline{\text{UPC}}_{it}$) is the employment-weighted value of UPC_{it} across other firms in the same industry. All regressions include firm, firm-age × year, and industry × year fixed effects, as well as a common post-adoption indicator for both treatment and control firms. Robust standard errors clustered by four-digit firm SIC are given in parentheses.

[a] An observation is a firm-year. Observation counts are rounded to comply with Census Bureau rules on disclosure avoidance.

** $p < .05$.

*** $p < .01$.

addition of numerous new departments and an approach to the early objective of one-stop shopping." We investigate this hypothesis using registered TM applications as a proxy for variety-increasing product innovation.

As a starting point, figure 6 presents aggregate time-series evidence from the grocery industry. The solid line shows annual new product introductions according to the periodical *New Product News*, and the dashed line shows the average number of SKUs per grocery store as reported in *Progressive Grocer*.[37] Both series are ocular reproductions of data reported in Sullivan (1997).[38] The dotted line is a count of new TM applications for grocery-related products that we constructed from the USPTO data.[39]

Figure 6 helps motivate a firm-level TM analysis in two ways. First, it shows that TM applications are strongly correlated with product introductions and the expansion in SKUs on retail shelves. This suggests that it is reasonable to use TM applications as a proxy for variety-expanding product innovation. Second, all three time series experience a trend break around 1980—roughly the time period when the UPC was diffusing

[37] New products and SKUs per store are not mechanically influenced by scanning. According to Sullivan (1997, 474), "Company representatives said that the increase could not be due to changes in their sampling (for example, an increase in the area of the country covered) or to the adoption of scanner systems by supermarkets (neither company relies on scanner-based data sources)."

[38] We resorted to this approach because her original data have been lost. The SKU series has a gap in coverage between 1972 and 1982, as shown in the figure.

[39] To restrict our count of TM applications to the grocery industry, we focus on applications with one or more three-digit Nice codes corresponding to food, beverages, pharmaceuticals, or paper products. We adjust for missing data in the years before 1977 using a procedure described in app. sec. A.4.

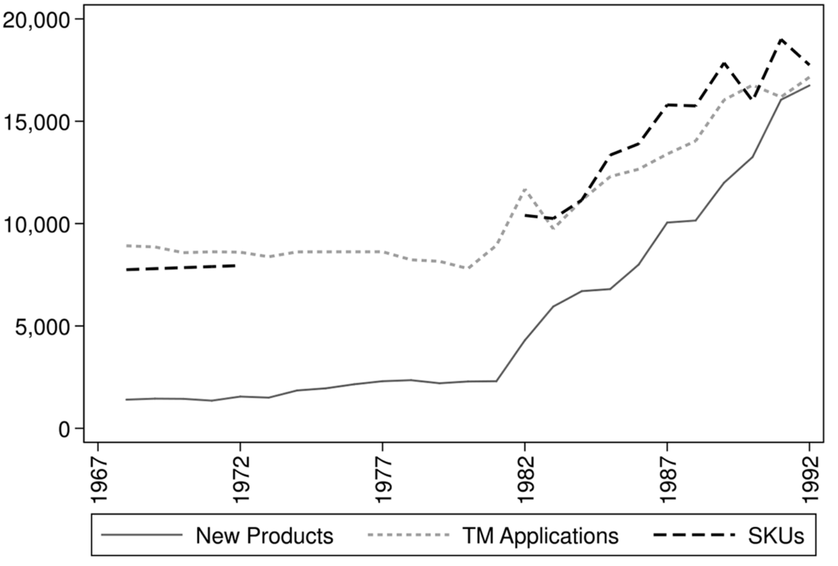

FIG. 6.—New product introductions, US TM applications, and average SKUs per store in the grocery industry. Sources: for new products and SKUs, Sullivan (1997); for TM applications, authors' calculations from USPTO Trademark Case Files Dataset. TM applications before 1977 are adjusted because of missing data (for details, see app. sec. A.4).

through the grocery supply chain, as illustrated in figure 3. This is consistent with the hypothesis that the UPC and related innovations encouraged grocery product proliferation and begs the question of whether increased trademarking is concentrated among firms that actually registered for a UPC.

Our firm-level TM analysis uses the difference-in-differences specification of equation (6). The outcome variable is an indicator that turns on if firm i files for one or more new TMs in year t. To address the selection effects observed above, we use previous TM registrations to create a matched sample. Each UPC adopter in the matched sample has a unique control. For firms observed for the first time in the year of registration, the controls are chosen at random from the set of firms of the same vintage. For firms aged 1–4 at the year of registration, the controls share a vintage and are matched on the cumulative number of TMs they have registered as of year $(t-1)$. For firms aged 5 and over at the year of registration, the controls are other firms that are at least 5 years old in year t, matched by the cumulative number of TMs they have registered between years $(t-5)$ and $(t-1)$. Results are presented in columns 5 and 6 of table 3.[40]

[40] The number of observations in the matched regressions differs from the number of observations in the matched regressions from columns 2 and 4 of table 3 because the matching procedure is different.

Estimates for both the full and the matched sample show a statistically significant 4.5 percentage point increase in the probability of trademarking following UPC registration. This effect is large relative to the 1.6% baseline probability of filing a TM but appears reasonable compared with the 20% annual filing probability for firms that registered at least one new TM during the sample period.

We also estimate an event-study specification for trademarking, based on equation (7) and using the matched sample to address potential selection effects. Figure 7 graphs the β_τ coefficients. By design, there is no preregistration trend difference between adopters and matched controls. The probability of TM registration steadily increases in the decade after UPC adoption; 10 years out, the probability of a TM registration is 13 percentage points higher than the counterfactual rate.

To summarize our firm-level analyses, we find that manufacturer UPC registration is associated with economically and statistically significant increases in employment, revenue, and TM registrations, whereas we find no relationship between UPC adoption and revenue-based TFP. Interpreting these results requires care. Although we use matching to remove

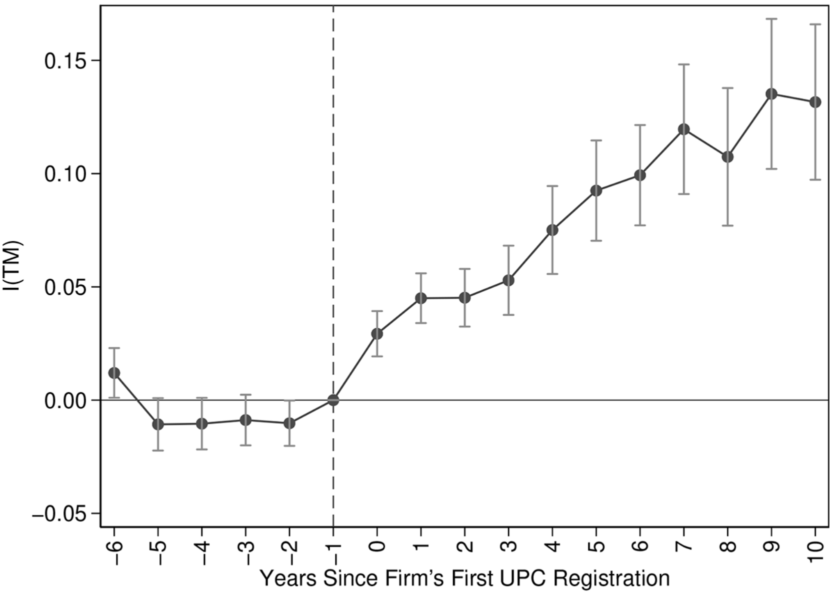

Fig. 7.—Matched-sample event study: TM registrations. Coefficient estimates and 95% confidence intervals are from an event-study regression of UPC adoption on the firm's current-year TM_{it} registrations. Control firms are a one-to-one match randomly drawn from all firms that do not adopt UPC before 1992, where matching is based on aggregate TM registrations over the preceding 5 years. Regression controls include firm, firm-age × year, and industry × year fixed effects, and a common set of pre- and postadoption indicators for both treatment and control firms.

selection effects and estimate a placebo event study to show that even fast-growing nonadopters from the same manufacturing industries do not exhibit similar outcomes, UPC adopters may still be more likely to adopt new technologies, use innovative management practices, and grow even in the absence of UPC adoption. Nevertheless, our findings suggest that once downstream technologies were in place, upstream UPC adoption helped manufacturers achieve scale by supplying large retailers. The TM results suggest that joint adoption of scanning and bar codes created new opportunities for producing and distributing a wider assortment of goods. The significance of these developments is illustrated by the role that both new retail formats and increased product variety played in later debates over aggregate price and productivity measurement (e.g., Boskin et al. 1998).

C. *International Trade*

Although several studies examine the link between importing and increased product variety (e.g., Feenstra 1994; Broda and Weinstein 2006), there is surprisingly little evidence linking import growth to changes in retail technology or productivity. Nevertheless, several observers such as Basker and Van (2010) and Raff and Schmitt (2016) suggest that technological innovations, including the UPC, were a key factor behind the growth in both imports and the scale of modern retail chains. If scanners and bar codes lower retailers' cost of managing a large assortment of goods, then imports are one channel through which they could obtain greater variety, complementing other channels such as adding domestic suppliers and exerting demand-side pressure on existing suppliers to increase their product offerings.[41] The UPC registration data allow us to examine this hypothesis by measuring the industry-level association between domestic retail technology adoption and international trade.

The outcome variables in our trade analyses are log US imports and import penetration, measured at the manufacturing industry-year level.[42] Our estimates are based on the following reduced-form specification:

$$\text{Trade}_{mt} = \alpha_m + \lambda_t + \beta\widehat{\text{UPC}}_{mt} + X_{mt}\theta + \varepsilon_{mt}, \tag{9}$$

where Trade_{mt} measures log imports or import penetration for industry m in year t, $\widehat{\text{UPC}}_{mt}$ represents the employment-weighted domestic industry UPC adoption in other industries that supply the same downstream retailers as

[41] Basker and Van (2007) offer a formal model of another potential channel linking UPC adoption to trade: technological changes that increase a chain's optimal size and lower its marginal input costs lead to lower prices, which stimulate demand. If contracting with offshore suppliers entails paying a fixed cost to purchase at a lower price, the chain will start importing when it reaches a minimum size threshold, at which point marginal cost again falls, leading to increased profits and pushing the chain to expand still further.

[42] Import penetration is defined as the following ratio: imports/(shipments + imports − exports).

industry m, α_m represents industry fixed effects, λ_t represents calendar-year fixed effects, and the error term ε_{mt} is clustered at the industry level. We also include time-varying industry-level controls, X_{mt}, for log industry value added, log capital-labor ratio, and the log ratio of production to nonproduction workers.

Our main explanatory variable, $\widehat{\mathrm{UPC}}_{mt}$ (alternatively, $\overline{\mathrm{UPC}}_{mt}$, employment-weighted UPC adoption in industry m), is based on adoption by domestic manufacturers. Although we do observe some UPC registrations with foreign addresses, it is unlikely that they reflect the full extent of foreign adoption, given that domestic firms can register for a UPC and have international suppliers print that domestic code on their packaging. More importantly, the domestic registration data are well suited to our purposes, because they can be mapped onto manufacturing industries. Given our previous results providing evidence of network effects in the diffusion process, we interpret domestic UPC registration in upstream industries as a proxy for adoption of scanners and related technology by retailers in the same supply chain.

The coefficient β in equation (9) measures the association between UPC adoption and trade. For imports, we expect this coefficient to be positive if scanning and supply-chain automation increase retailers' benefits from (or reduce their cost of) working with foreign suppliers. However, a positive coefficient could also reflect several different mechanisms, including (*a*) substitution of imported for domestic final goods, (*b*) an output-expanding effect if retailers expand their selection, (*c*) an output-expanding effect if retailers pass through lower prices to consumers, and (*d*) increased imports of intermediate goods as foreign manufacturers begin to supply components to domestic producers. It is less clear what we should expect for exporting. Because the UPC is a domestic standard, it is tempting to view exports as a placebo test. In practice, our estimates of the relationship between domestic UPC adoption and exports are statistically insignificant and close to zero in almost all specifications, so we focus on the import regressions.

Table 5 presents the results of our trade regressions. Across all four models, we find a statistically significant positive relationship between domestic UPC adoption and imports. The magnitude of the coefficients implies that a 1 standard deviation increase in industry-level UPC adoption is associated with a 6%–7% increase in imports.[43] This result is robust to dropping Canadian imports (which might be influenced by the 1988 Canada–United States Free Trade Agreement) and also two different approaches to excluding trade in intermediate goods.[44]

[43] The within-industry standard deviation of $\overline{\mathrm{UPC}}_{mt}$ is approximately 0.125.

[44] To exclude intermediates, we limit the estimation sample to the set of manufacturing industries in our concordance between CRT lines and SIC codes (described in app. sec. A.3), which clearly sell some products through retail channels. We also tried excluding intermediate-goods imports based on data from Schott (2004) that classifies any HS code containing the word "parts" or a related term as an intermediate. These results are not reported but are qualitatively similar to reported results.

TABLE 5
EFFECT OF UPC ADOPTION ON INDUSTRY-LEVEL TRADE

	Imports		Import Penetration	
$\widehat{\text{UPC}}_{mt}$	.7698***		.2766***	
	(.3227)		(.0480)	
$\overline{\text{UPC}}_{mt}$		.5204***		.0549***
		(.1346)		(.0143)
Controls[a]	✓	✓	✓	✓
Observations[b]	7,596			

NOTE.—The table shows difference-in-differences regressions of industry-level UPC adoption on trade. Imports are logged. Import penetration is the ratio of imports to (shipments + imports − exports). $\widehat{\text{UPC}}_{mt}$ represents the employment-weighted UPC adoption in other industries that supply the same downstream retailers. $\overline{\text{UPC}}_{mt}$ represents the employment-weighted UPC adoption in industry m. Robust standard errors clustered by SIC are given in parentheses.

[a] All regressions include industry and year fixed effects and controls for log (domestic) industry value added, log capital-labor ratio, and log production-to-nonproduction worker ratio.

[b] An observation is an industry-year.

*** $p < .01$.

There are several reasons to be cautious about the trade results. In one sense, it is clear that the estimates are not causal: adding numeric codes to domestic producers' packaging should not cause an increase in imports. If we interpret UPC adoption as a proxy for supply-chain automation and the reconfiguration of retail distribution channels, there remains a strong likelihood of selection on the gains to treatment. That is, bar codes were probably adopted first in the industries where they were most useful, such as food, pharmaceuticals, and apparel, and would likely have less impact (or perhaps altogether different impacts) when adopted by manufacturers of industrial goods or heavy equipment. Finally, causality could run in either direction. If trade and technology are complementary inputs to the retail production function, an exogenous increase in imports (e.g., because of tariff reductions) could stimulate domestic technology adoption.

In spite of these concerns, we believe that these regressions provide some of the first evidence directly linking import growth to changes in retail technology. Moreover, the correlation between imports and domestic UPC adoption also points to the broad impacts of the entire system of technologies supported by the adoption of UPCs and scanning.

VI. Concluding Remarks

Bar codes were a key component in a broad set of innovations that dramatically lowered the cost of managing inventory in retail supply chains. Scholars have suggested that this had far-reaching implications, including the rise of the big-box format (e.g., Dunlop 2001; Holmes 2001) and subsequent increases in industry concentration (e.g., Basker, Klimek, and Van 2012; Hsieh and Rossi-Hansberg 2019). This paper is the first to measure the effects of UPC adoption on upstream employment, revenue, product innovation, and industry-level imports, providing a natural complement to the literature on retail productivity (e.g., Foster, Haltiwanger, and Krizan 2006; Basker 2012) and a new addition to the empirical literature on the effects of industry standards.

We show that early UPC adoption is strongly correlated with firm size and that the timing of UPC adoption varied across industries. Many large food and drug manufacturers had already adopted the UPC by the mid-1970s, whereas adoption by apparel, furniture, and textile manufacturers remained at low levels into the early 1980s. This pattern is consistent with the idea that upstream UPC adoption was driven by (the expectation of) downstream installation of complementary scanning technology, which began in the grocery industry and was later implemented in other industries. We provide new evidence on this point by estimating a reduced-form model of network effects in UPC adoption, and we find strong evidence of positive spillovers among manufacturers that sell through the same distribution channels.

Our investigation of the impacts of UPC adoption suggests that both upstream and downstream firms benefited on several margins. For manufacturers, we find that both revenue and employment increased with and following adoption, consistent with receiving larger orders from retailers. The timing of the employment effects revealed by our matched-sample event-study regressions suggests that UPC adoption is associated with business diversion, whereby manufacturers integrate into the supply chain of large downstream retailers. These findings help explain why manufacturers embraced the UPC, even if the productivity benefits were expected to accrue mostly to retailers. Early adopters sought to prevent standards fragmentation, whereby each large retailer would require its suppliers to use a proprietary symbol. Later on, particularly after Kmart and Walmart required their suppliers to bar code all items, the pressure from the demand side became explicit. Our results show that manufacturers benefited from UPC adoption through increased orders and that these benefits grew as UPC proliferated through the retail channel.

The downstream effects of UPC adoption are harder to assess. Retail productivity growth presumably reflects the direct benefits of scanning, as well as the increased scale and scope made possible by UPC and complementary technologies. Because we do not have explicit data on buyer-supplier relationships, we cannot directly test the hypothesis that upstream UPC adoption increases downstream store size or selection. Time-series evidence, however, supports the idea that the retail sector responded to the UPC by increasing store assortment. For example, we show that the rate of growth in unique products (SKUs) stocked by supermarkets, the number of new product introductions in the grocery industry, and the number of new TM applications filed by food and grocery manufacturers all increased dramatically starting in the early 1980s, as bar codes and scanners became pervasive within that distribution channel. Moreover, we show that the increase in trademarking is disproportionately due to firms that registered for a UPC, suggesting a direct link between improved supply-chain coordination and increased new-product variety. Finally, the positive correlation between UPC adoption and industry-level imports points to broader effects of the entire bar-code system, including its role in enabling automated inventory tracking and replenishment, which encouraged large retail chains to seek out more international suppliers.

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