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An empirical study of RFID productivity in the U.S. retail supply chain

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ABSTRACT

Radio Frequency Identification, or RFID, technology has received great attention when, beginning in 2003, Walmart announced its plan to use the technology. RFID's automatic scanning ability can reduce product scanning error rates and product scanning manpower, which can lead to increased labor productivity. This paper evaluates labor productivity of RFID adopted retailers. This paper uses data from financial statements and explains the association between RFID technology and adopted retailer's labor productivity. The regression analysis using the Cobb–Douglas production function shows that RFID retailers have a higher labor to gross income elasticity than their non-RFID counterpart, indicating that RFID retailers have higher labor productivity.

1. Introduction

Productivity is defined as a ratio of outputs to inputs, and efficiency is measured by the ratio of observed output to the maximum potential output that can be obtained from inputs (Fried et al., 2007). Productivity measures companies' efficiency in generating outputs with limited input resources, and it can be used to compare companies in the same industry. Maintaining high productivity is a key to maintaining high profitability on a long-term basis. Based on a report by National Retail Federation (JD Associates, 2011), the following are commonly used key performance indicators (KPIs) in the retail industry: sales, customer returns, transaction counts, labor costs, inventory-to-sales ratio (ISR), inventory turnover ratio (ITR), return on capital employed (ROCE), and gross margin return on investment (GMROI). Although there are many indicators, there is a challenge in measuring retail productivity because of the retail industry's intangible characteristics of outputs and inputs.

RFID technology, a wireless Automatic Identification and Data Capture (AIDC) technology (Fosso Wamba et al., 2008), received great attention in the U.S. retail supply chain when Walmart announced its plans to use RFID beginning in 2003. RFID technology is a global phenomenon that began in the U.S. retail industry. Walmart was the first to issue RFID technology mandates, which required its top 100 suppliers to put RFID tags on their pallets and cases beginning in January 2005 and to charge Sam's Club suppliers a $2 penalty per pallet without a RFID tag (Hunt, 2007). Walmart's RFID initiative is refocused on Electronic Product Code (EPC) Gen 2 RFID tag, which became an industry-wide RFID technology standard (Roberti, 2010). While Walmart's initial effort has been focused on IT integration with pallet level RFID tagging, its recent effort since 2010 has been to investigate item-level RFID tagging (Roberti, 2014).

Like the U.S.'s Walmart, in Europe, Metro AG (Germany) and Tesco (U.K.) began to implement the RFID technology in 2003 and 2004, respectively. Marks and Spencer (U.K.), Carrefour (France), and Ahold (Netherlands) followed suit with RFID mandates of their own (OECD, 2008). Metro Group announced that some penalty would be imposed on the suppliers without RFID technology (EUJRC, 2007) as Walmart did. In addition, the EU Commission adopted the Track and Trace Directive requiring food and beverages to have complete catalogs of anything with the final product for its quality and safety (EUJRC, 2007). RFID tags with temperature sensors can provide this traceability and safety requirement. This requirement is similar to the U.S.'s FDA mandate to use RFID technology for tracking pharmaceutical products.

Use of RFID technology can improve inventory operation efficiency and supply chain efficiency, which can improve productivity of retail companies. However, there is uncertainty about RFID's return on investment (ROI), and the RFID-adoption rate slowed after 2007 (Edwards, 2008). In addition, small and medium enterprises (SMEs) hesitate to adopt RFID technology because they perceive investment in RFID technology risky. While large enterprises are likely to enjoy the economies of scale in RFID implementation, SMEs claim that RFID technology is cost-ineffective because of high up-front implementation cost (EUJRC, 2007; Lee and Lee, 2010).

Many academic papers (Leung et al., 2007; Visich et al., 2009; Rekik et al., 2009; Sarac et al., 2010; Zhu et al., 2012; Bhattacharya,

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2012) argue that there are many advantages for RFID adoption: (1) cost saving, (2) revenue increase, (3) inventory management efficiency, and (4) productivity increase. RFID investments enable labor productivity improvements by eliminating manual processes. Decreases in labor cost can be achieved by reducing the physical counting of inventory and product scanning-error rate. Revenue increases can be made by prevention of theft, shrinkage, and inventory write-off as well as decreased counterfeiting and decrease in returns (Veeramani et al., 2008). RFID adoption can also allow improved inventory management accuracy and responsiveness through real time inventory information.

The Cobb–Douglas production function is a well-known economic theory that explains the relationship of outputs with two inputs, labor and capital. Even when this function is developed with only two input factors, it is still widely used for measuring productivity. This paper, using the Cobb–Douglas production function, investigates the effects of RFID technology on the labor productivity of the U.S. retail supply chain. The following is the research hypothesis to test whether RFID adoption gives benefits to adopting retailers in productivity.

H: *A significant relationship exists between labor input with RFID technology for retail companies and their productivity*.

This study is organized as follows: First, the authors provide a brief literature review and a short summary of Cobb–Douglas production function. Then, they discuss the research approach, which includes data collection procedure and research methods. After providing outputs, the study ends with a brief discussion section and a conclusion section.

2. Literature review

2.1. Studies on RFID adoption effect

Among the various adoption effects mentioned in the introduction section, operational efficiency and cost savings are two main effects of RFID technology in the retail industry. Visich et al. (2009), Sarac et al. (2010), Bhattacharya (2012), and Zhu et al. (2012) analyze existing academic papers about companies adopting RFID technology and use content analysis to find RFID retailer benefits: better management of inventory, improved security, increased operational efficiency, increased visibility, and reduced cost. Soon and Gutierrez (2008) argue that retailers have the power to force the adoption of RFID technology in their supply chain networks because the retailers have more significant benefits than the manufacturers in reduced inventory, lower labor costs, and stockout reduction.

Hardgrave et al. (2008) studied the accuracy of inventory records with RFID tags in 24 Walmart stores. According to their reports, the retailers' average stockout rate was 8%, and 4% of annual sales were expected to be reduced because of those stockouts. Hardgrave et al. (2013) study how accurate inventory records are when RFID tags are used. According to their experimental study with five product categories (air-care products, floor-care products, formula, DIY furniture, and quick cleaner), RFID technology decreases inventory record inaccuracy (IRI) by 26%. Among the five categories, all but DIY furniture improve in IRI.

There are a few papers (Jeong and Lu, 2008; Chang, 2011; Shin and Eksioglu, 2014a; Shin and Tucci, 2015) about the relationship between RFID adoption and its financial performance. Jeong and Lu (2008) investigate the impact of RFID investment announcement on the market value of RFID adopted companies and find that there is a positive abnormal return on RFID investment. Chang (2011) examines the relationship between RFID technology adoption and U.S. firms' financial performances. He finds that RFID technology offers significant benefits of improved inventory ratios, sales efficiency, and higher profitability. Shin and Eksioglu (2014a) study the effect of RFID adoption on efficiency and profitability in U.S. retail supply chains. They find that RFID retailers have significantly lower days-in-inventory ratio and per-employee costs. They also argue that RFID adoption leads to a positive relationship with gross margin increase. Shin and Tucci (2015) investigate Walmart's RFID initiative effect in the 21st century. They find, although Walmart has improved its efficiency with respect to inventory management, Walmart did not show improved financial performance associated with supply chain management against its competitors.

There are several papers (EUJRC, 2007; Leung et al., 2007; Rekik et al., 2009; Sarac et al., 2010) that correlate labor-cost savings with an adoption of RFID technology, which can lead to improved labor-productivity. Their conclusion comes from subjective data which is produced by their survey. To the best of our knowledge, this is one of the first empirical studies with objective data that rigorously examines labor-productivity of U.S. retailers with RFID technology.

2.2. Studies on retail productivity

Measuring productivity is a challenge in the retail industry, because no consensus on the proper measures of retail inputs and outputs has been established (Manser, 2005). Reynolds et al. (2005) discuss the concept of output in the retail sector. Since retail output includes a large service element, labor productivity is measured by the gross value added for each worker. Dawson (2005) shows that retail output is different from that of manufacturing because retail is spatially disaggregated and networked. The efficiency of the network's operation with large numbers of suppliers is a critical factor impacting retail productivity. Foster et al. (2005) discuss the massive restructuring in the U.S. retail trade industry during the 1990s with the intensive adoption of information technology, including inventory control, scanning, and credit card processing, which contributes to productivity growth in the U.S. retail sector.

Reardon and Vida (1998) compare monetary and physical measures of productivity inputs using Cobb–Douglas production functions. They suggest capital input measures such as square footage of space, dollar value of assets, rent, or the insured value of the establishment. The study suggests that labor input measures should be (1) the number of employees or time worked by employees or (2) the amount of money paid to employees. They find that monetary measures are empirically equal to physical measures of retail inputs. Reardon and Vida (1998) also suggest some output measures for retail industry: (1) gross sales, (2) number of transactions, or (3) value added. Griffith and Harmgart (2004) define value added in the retail industry as output minus the cost of goods sold and other intermediate inputs. Baldwin and Gu (2011) use the trade margin, which is a value-added output in the retail industry. In general, sales and gross income, sales less the cost of goods sold, are commonly used output measurements in the retail industry (Manser, 2005).

Because RFID investment is an IT investment, previous studies about relationship between IT investment and retail supply chain productivity give a theoretical background for RFID's productivity study. There have been some studies about IT productivity of the retail industry: Cachon and Fisher (2000) find that information sharing through IT investment leads to higher performance of retail supply chain costs; Carr (2003) argues that firms' IT spending does not guarantee superior financial results. Shah and Shin (2007) investigate the relationship among IT investment, inventory, and financial performance with retail industry data of 1960–1999. They find no studies between IT investment and financial performance in retail industry but IT investment improves inventory performance which leads to a positive financial performance. Their conclusion is that there exists an indirect effect on financial performance through inventory management from IT investment.

2.3. Studies on RFID implementation issues

There are several issues regarding adoption of RFID technology: standardization issues, economic issues, system integration and inter-organization issues, and social issues. Panizza and Lindmark (2010) argue that the lack of a global standard prevents companies from interoperability. The standardization of RFID tags and EPC, a global product identifier, is a main issue associated with adopting RFID. Use of standard RFID technology across an overall supply chain is a critical factor for streamlined flow of information among the partners in the same supply chain (Matta et al., 2012). International Organization for Standardization (ISO) and the industry consortium EPCglobal are two main organizations supporting RFID standardization. There are four frequency ranges used for RFID communications: LF, HF, UHF, and Microwave. UHF frequency ranges used in the U.S. are incompatible with those used in Europe. While Europe assigns 860–960 MHz, the U.S. uses 902–928 MHz. In addition, because RFID is operated in unlicensed bands, there is a possibility for radio frequencies to make conflicting signals (EUJRC, 2007).

Investment costs for RFID technology associated with uncertainty of return on investment are a major barrier for adoption of RFID technology. According to Sarac et al. (2010), there are six components of RFID implementation costs: (1) hardware costs, (2) software costs, including database system, interface system, and middleware system, which extract the data from RFID readers, filter the data, aggregate the information, and route the data to enterprise systems (EUJRC, 2007), (3) system integration costs with an existing Enterprise Resource Planning (ERP) system, (4) installation service cost, (5) personnel costs (user training) , and (6) business process re-engineering costs. Integration of existing software with RFID information alone will cost more than the cost of RFID hardware (EUJRC, 2007). In addition, investment in a new RFID system requires complementary investments including network technologies, which provide communications between RFID readers and backend systems. Therefore, initial implementation cost and lack of evidence of strong ROI are main economic issues regarding RFID adoption. According to Gaukler (2011), in the three echelon supply chain, while a positive ROI exists for retailers, there is no positive ROI of item-level tagging for manufacturers. Therefore, levels of implementation, such as item-level, case-level or pallet-level, are another issue the partners in a supply chain need to agree upon.

According to Whitaker et al. (2007), appropriate information technology infrastructure, i.e., ERP, is a pre-requisite for successful RFID implementation because most benefits of RFID data come from reliable and suitable use of data produced by RFID systems and sharing that data among the supply chain partners. They find that RFID implementation spending, even if it is caused by a partner mandate, is positively associated with early return on RFID investment. Collaborative excellence among the supply chain partners is a crucial factor for extending supply chain efficiency, thus system integration among the supply partners is a big hurdle to overcome because usually each supply partner has its own existing system. Therefore, fair sharing of costs and benefits of RFID technology adoption between supply chain partners is important (Panizza and Lindmark, 2010).

In addition to the economic, technical, and organizational issues, there is a social issue to accept the RFID technology. According to the report by the EU Joint Research Centre (EUJRC, 2007), a major drawback to wide-spread development of RFID systems is resistance of social acceptance and potential distrust of RFID technology, which is a result of insufficient privacy and security safeguards. Because anyone can scan a RFID tag if the tag is accessible by a reader, customer privacy is a big concern for retailers with RFID technology (Zhu et al., 2012).

3. Theoretical background

As explained earlier, the Cobb–Douglas production function is widely used to represent the relationship between an output and two inputs, capital (K) and labor (L) . It was tested for statistical evidence with U.S. manufacturing industry data by Cobb and Douglas in 1928 (Hong, 2008). The assumptions in the Cobb–Douglas production function are (1) if either labor or capital vanishes, then so will production, (2) the marginal productivity of labor/capital is proportional to the amount of production per unit of labor/capital. The function has the following form:

$$P(L,K) = AL^{\alpha}K^{\beta} \tag{1}$$

where P is the total production, L the labor input, K the capital input, A the total factor productivity, α the output elasticity of labor, and β the output elasticity of capital.

Total production refers to the monetary value of all goods and services produced in a year. Hours worked by full-time employees and fixed assets are usually used to generate labor and capital inputs. Total factor productivity (TFP) is "the portion of output not explained by the amount of inputs used in production" (Comin, 2006). TFP is assumed to be a constant which is independent of both labor and capital. Output elasticity measures the change of output to a change of labor or capital (Hong, 2008), where α denotes output elasticity of labor, and β denotes output elasticity of capital.

RFID companies assume that when the RFID technology is introduced, operation costs will lessen and the workers' efficiency will increase. With this assumption, γ, the output elasticity of labor with RFID technology is added to Eq. (1) to find the labor productivity with RFID technology:

$$P(L,K) = AL^{\alpha+\gamma \mathrm{RFID}}K^{\beta} \tag{2}$$

In Eq. (2), "RFID" is a dummy variable that takes the value "1" if a retail company adopts the RFID technology and "0" otherwise. Thus, the output elasticity of labor for RFID companies (RFID=1) is $\alpha+\gamma$, and for non-RFID companies (RFID=0) it is α. Applying the log transformation to Eq. (2), the following equation is produced:

$$\ln(P(L,K)) = \ln(A) + \alpha \ln(L) + \beta \ln(K) + \gamma \text{ RFID} \ln(L) \tag{3}$$

In Eq. (3) , output elasticity of each input (α, β,γ) becomes a coefficient of log-transformed variables, i.e., if labor factor (L) of RFID retail companies increases by 1% while capital factor (K) is held constant, the total production, $P(L,K)$, will change by $(\alpha+\gamma)$%.

4. Data collection

RFID technology diffusion is categorized into three phases by institutional analysis (Yang et al., 2008): (1) Emergence phase starts with Auto-ID Labs in 1999, which is a research group for the RFID and emerging sensing technology, (2) Structuralization phase starts with Walmart's first RFID mandate in 2003, and (3) Evolution phase starts with EPC Gen 2 RFID tag being announced in 2005. The first EPC Gen 2 RFID tag was introduced in April 2005, and Walmart and Target launched a shared pilot test with this tag in October 2005. Finally, ISO approved the EPC Gen 2 standard in July 2006, which affirmed EPCglobal standard as an industry-wide, global standard for RFID technology.

One of the U.S. Security and Exchange Commission (SEC) regulations is that the publicly traded companies in the U.S. stock market must publish their investments which could affect their capital structure (Jeong and Lu, 2008). Companies listed in the U.S. stock market announce their RFID investment in their annual report and press releases. The three previous studies (Jeong and Lu, 2008; Chang, 2011; Shin and Eksioglu, 2014b) of RFID adoption effect on profitability use financial statements of RFID adopted companies listed in the U.S. stock market. Chang (2011) chooses three year data (2003–2005) of 62 U.S. manufacturing companies with RFID technology. Jeong and Lu (2008) choose six year data (2001–2006) of U.S. companies which make their RFID investment announcement. There were 128 RFID investment announcements between 2001 and 2006 and 86% of them were announced between 2004 and 2006. Shin and Eksioglu (2014b) choose four year data (2008–2011) of U.S. retail companies with RFID technology. We use the same methods as the previous three studies to find an RFID investment announcement. The 25 RFID adopted retail companies are selected by keyword searching in various databases such as Google keyword database, an article database from RFID Journal and article databases from online magazines of supply chain/logistics/retail, and press release database from BusinessWire. The cumulative number of RFID adopted retail companies was 9 in 2005, 19 in 2006, 22 in 2007, 24 in 2010, and 25 in 2013. Since 2007, the number of cumulative retail companies with RFID adoption has been stable (see Fig. 1) . Considering the RFID technology standardization status, the RFID diffusion stages, and the cumulative number of RFID adoption companies, the data are collected for seven years from 2007 through 2013.

The companies are selected with two criteria: (1) each retail company is listed in U.S. stock markets such as NYSE or NASDAQ, and (2) each has complete financial data with a number of full-time employees from 2007 through 2013. NAICS, the North America Industry Classification System, is the U.S. industry classification standard used in the federal statistics. The companies in the U.S. retail industry have a NAICS code beginning with 44 and 45. Between 2007 and 2013, there were 267 U.S. companies in Compustat database that have an industry sector in retail. Among them, 122 companies are selected based on the above two criteria. The total number of observations in the data is 854, i.e., 122 companies over 7 years.

5. Regression models and results

5.1. Pooled regression model

Pooled regression analysis is combined for several cross-sections with data of repeated observations on fixed units (Podesta, 2002). Pooled regression analysis ignores time series dimension and it considers data as a cross-section dimension. In this section, Eq. (3) is used to estimate labor productivity of retail companies. According to the Organization for Economic Co-operation and Development (OECD) labor statistics, U.S. employees work for less than 1800 h per year. Table 1 shows the annual average number of working hours for U.S. workers from 2007 through 2013.

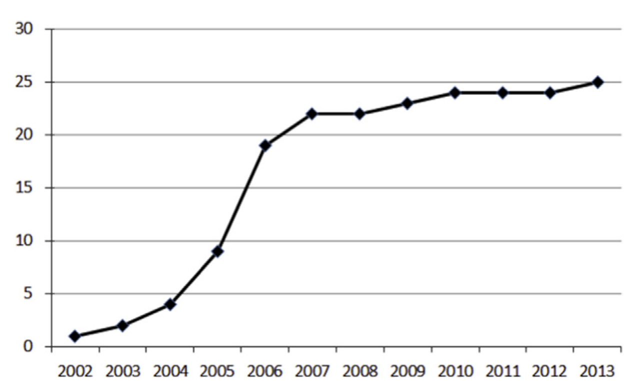

Fig. 1. Cumulative number of RFID companies.

The product of the number of full-time workers per company (EMP) and average annual working hours (WH) is the total number of hours worked at a company per year. This product (EMP-WH) and fixed assets (FA) are used for labor input (L) and capital input (K), respectively.

As many articles mentioned (Reardon and Vida, 1998; Griffith and Harmgart, 2004; Reynolds et al., 2005; Manser, 2005; Dawson, 2005; Baldwin and Gu, 2011), estimating total production in the retail industry is challenging due to intangible output measures. For example, the output of retail industry is typically a product which is a combination of physical items and various services such as assembly, display, delivery, warranty, and/or installation. There are two common output measures in the retail industry: sales and gross income (Ingene and Lusch, 1999; King and Park, 2004; Manser, 2005). While the U.S. Bureaus of Labor Statistics uses sales, the U.S. Census Bureau uses gross income as a measure of retail output (King and Park, 2004). In this study, gross income (GI) is used for the output in the production function. To estimate the production functions of U.S. retail industries, these three variables (GI, EMP-WH, and FA) are substituted into Eq. (3):

$$\ln(\mathrm{GI}_{it}) = \ln(A) + \alpha \ln(\mathrm{EMP{-}WH}_{it}) + \beta \ln(\mathrm{FA}_{it}) + \gamma \mathrm{RFID}_{it} \ln(\mathrm{EMP{-}WH}_{it}) + \epsilon_{it} \tag{4}$$

where EMP-WH equals the number of full-time employees multiplied by the annual average working hours, FA = the fixed assets, GI the gross income, for each company $i=1,\ldots,122$ and each year $t=2007,\ldots,2013$.

Table 2 presents output from the pooled regression model. The R^2 is very high (0.9263) and p-values of model fit and coefficients are significant at the 1% level. When the Cobb–Douglas production function was studied in 1928, constant return to scale (CRS) was assumed, i.e., $\alpha+\beta=1$, which means that the output change is proportional to the input change. Therefore, the ranges of α and β should be between 0 and 1. The coefficients of this model, $\alpha=0.4273$ and $\beta=0.3886$, are within the acceptable ranges. The pooled regression model needs to be tested for the assumption of homoskedasticity and no serial correlation. The *p-value* in the Breusch–Pagen (BP) test is 0.0002, which means that

Table 1
Average annual working hours per U.S. worker.

Year	2007	2008	2009	2010	2011	2012	2013
Annual work hours	1797	1791	1767	1777	1786	1789	1788

Source: OECD Labor Statistics (http://stats.oecd.org/Index.aspx?DatasetCode=ANHRS)

Table 2
Results from the pooled regression model.

R^2	*F-Stat* (*p-value*)	Degrees of Freedom (DoF)	Intercept (*p-value*)	α (*p-value*)	β (*p-value*)	γ (*p-value*)
0.9263	3654 (0.000)	3850	5.4489 (0.000)	0.4273 (0.000)	0.3886 (0.000)	0.0138 (0.000)

homoskedasticity assumption is rejected at 1%. The Durbin–Watson (DW)d statistic is 0.4320, which means there is autocorrelation. The VIF values of three variables are 5.3708, 5.4163, and 1.5970, i.e., the data show no strong multicollinearity. To overcome the autocorrelation problem, two panel data regression approaches are offered: fixed effect and random effect. According to Greene (2012), while the fixed effect assumes that individual heterogeneity is correlated with independent variables, the random effect assumes that the individual heterogeneity is uncorrelated with the independent variables. Jerry A. Hausman developed

Table 3
Test statistics and results.

Test name	Test values	Critical values	Results
Breusch–Pagan (BP)	$BP = 19.6653$ $p\text{-}value = 0.0002$	$\alpha = 0.01$	Hetroskedasticity
Durbin–Watson (DW)	$DWd = 0.4320$ $p-value < 2.2e-16$	$dL(n=850,\ \alpha=0.01,\ k=4) = 1.83365$ $dH(n=850,\ \alpha=0.01,\ k=4) = 1.84779$	Autocorrelation
Hausman (H)	$Chi\text{-}square = 40.7130$ $p\text{-}value = 7.523e-09$	$\alpha = 0.01$	Fixed effect
VIF	5.3708[a] 5.4163[b] 1.5970[c]	10	No strong multicollinearity

[a] $\ln(\text{EMP}-\text{WH}_{it})$.
[b] $\ln(\text{FA}_{it})$.
[c] $\text{RFID}_{it}\ \ln(\text{EMP}-\text{WH}_{it})$.

Table 4
Test statistics and results.

Model	Regression model
FEM1	$\ln(\text{GI}_{it}) = \ln(A) + \alpha\ \ln(\text{EMP}-\text{WH}_{it}) + \beta\ \ln(\text{FA}_{it}) + \gamma \text{RFID}_{it}\ \ln(\text{EMP}-\text{WH}_{it}) + \epsilon_{it}$
FEM2	$\ln(\text{GI}_{it}) = \ln(A) + \mu_i D_i + \alpha\ \ln(\text{EMP}-\text{WH}_{it}) + \beta\ \ln(\text{FA}_{it}) + \gamma \text{RFID}_{it}\ \ln(\text{EMP}-\text{WH}_{it}) + \epsilon_{it}$
FEM3	$\ln(\text{GI}_{it}) = \ln(A) + \mu_i D_i + \mu_t T_t + \alpha\ \ln(\text{EMP}-\text{WH}_{it}) + \beta\ \ln(\text{FA}_{it}) + \gamma \text{RFID}_{it}\ \ln(\text{EMP}-\text{WH}_{it}) + \epsilon_{it}$
FEM4	$\ln(\text{GI}_{it}) = \ln(A) + \mu_i D_i + \alpha\ \ln(\text{EMP}-\text{WH}_{it}) + \alpha_i D_i\ \ln(\text{EMP}-\text{WH}_{it}) + \beta\ \ln(\text{FA}_{it}) + \gamma \text{RFID}_{it}\ \ln(\text{EMP}-\text{WH}_{it}) + \epsilon_{it}$
FEM5	$\ln(\text{GI}_{it}) = \ln(A) + \mu_i D_i + \alpha\ \ln(\text{EMP}-\text{WH}_{it}) + \alpha_i D_i\ \ln(\text{EMP}-\text{WH}_{it}) + \beta\ \ln(\text{FA}_{it}) + \beta_i D_i\ \ln(\text{FA}_{it}) + \gamma \text{RFID}_{it}\ \ln(\text{EMP}-\text{WH}_{it}) + \epsilon_{it}$
FEM6	$\ln(\text{GI}_{it}) = \ln(A) + \mu_i D_i + \mu_t T_t + \alpha\ \ln(\text{EMP}-\text{WH}_{it}) + \alpha_i D_i\ \ln(\text{EMP}-\text{WH}_{it}) + \alpha_t T_t\ \ln(\text{EMP}-\text{WH}_{it}) + \beta\ \ln(\text{FA}_{it}) + \beta_i D_i\ \ln(\text{FA}_{it}) + \beta_t T_t\ \ln(\text{FA}_{it}) + \gamma \text{RFID}_{it}\ \ln(\text{EMP}-\text{WH}_{it}) + \epsilon_{it}$

Table 5
Results from the pooled regression model.

Method	BP p-$value$[a]	DWd	R^2	F-Stat p-$value$	DoF	$\ln(A)$ p-$value$	α p-$value$	β p-$value$	γ p-$value$
FEM1	0.0002	0.432	0.9263	3564.0 (0.000)	3850	0.5449 (0.000)	0.427 (0.000)	0.389 (0.000)	0.014 (0.000)
FEM2	0.0000	1.371	0.9919	717.6 (0.000)	124,729	4.6248 (0.000)	0.765 (0.000)	0.124 (0.000)	0.005 (0.000)
FEM3	0.0000	1.386	0.9926	744.3 (0.000)	130,723	5.593 (0.000)	0.713 (0.000)	0.119 (0.000)	0.002 (0.254)
FEM4	0.0007	1.868	0.9951	499.9 (0.000)	245,608	3.059 (0.009)	0.649 (0.000)	0.308 (0.000)	0.004 (0.012)
FEM5	0.0135	2.121	0.9969	422.3 (0.000)	366,487	4.482 (0.341)	0.484 (0.313)	0.372 (0.095)	0.002 (0.747)
FEM6	0.0014	2.180	0.9974	463.3 (0.000)	384,469	11.698 (0.000)	0.156 (0.310)	0.272 (0.000)	0.001 (0.443)

[a] These p-$values$ are from HC standard errors.

a test for determining which approach is appropriate. With the Hausman test, the null hypothesis is rejected with *p-value*=7.523e−09. Therefore, the preferred model is the fixed effect model. Table 3 summarizes the test statistics of the pooled regression model.

5.2. Fixed effect regression model

Baltagi (2005) explains a procedure to estimate the fixed effect regression model. The model adds some dummy variables (intercept and slope) in each step. Since the panel data in this study has two dimensions, the dummy variables used in this model are dummy variables for both individual company (D_i) and fiscal year (T_t). For example, D_i and T_t are intercept dummy variables for each retailer and year, respectively, and ($\text{EMP}-\text{WH}_{it}*D_i$), ($\text{FA}_{it}*D_i$), ($\text{EMP}-\text{WH}_{it}*T_t$) and ($\text{FA}_{it}*T_t$) are productive forms of slope dummy variables. The following are a list of procedures to build the fixed effect models (FEMs):

- *FEM*1: Pooled regression model with no dummy variables.
- *FEM*2: Adding individual intercept dummy variables (D_i) to FEM1.
- *FEM*3: Adding time intercept dummy variables (T_t) to FEM2.
- *FEM*4: Adding individual slope dummy variables for the first independent variable ($\text{EMP}-\text{WH}_{it}*D_i$) to FEM2.
- *FEM*5: Adding individual slope dummy variables for the next independent variable ($\text{FA}_{it}*D_i$) to FEM4.
- *FEM*6: Adding time intercept dummy variables (T_t) and time slope dummy variables ($\text{EMP}-\text{WH}_{it}*T_t$ and $\text{FA}_{it}*T_t$) to FEM5.

Table 4 presents the six fixed effect models. There are 121 intercept dummy variables for individual companies and 6 time intercept dummy variables. In addition, there are 121 individual slope dummy variables for EMP-WH and FA and 6 slope time dummy variables for EMP-WH and FA. The total number of dummy variables that are used in FEM6 is 381.

Table 5 presents the results of the six FEMs. The *p-values* of FEMs except FEM5 from the *BP* tests are near zero, so the five models qualify as heteroskedastic. The problem with heteroskedasticity is that the *T-statistics* of coefficients cannot be relied upon because the estimated standard errors are biased. The heteroskedasticity-consistent (HC) standard errors were proposed by Halbert White to fit models with heteroskedastic residuals and correct standard errors (White, 1980). The *p-values* of coefficients in the five FEMs are based on HC standard errors. FEM4 through FEM6 do not have autocorrelation problems because their Durbin–Watson (*DW*)*d* values are greater than *dL*(1.84779). In the *DWd* statistic table (http://www.stanford.edu/clint/bench/dwcrit.htm), there is no *DWd* value for 854 observations, thus the most similar number was chosen, i.e., 850 observations with 1% significance level. Considering *p-values* of coefficients in FEM4 through FEM6, only FEM4 is acceptable. Coefficients of independent variables in FEM4 are significant at α=1%, $\beta=1\%$, and $\gamma=5\%$ and overall fit of the regression model is significant at the 1% level. RFID companies ($\alpha+\beta$=0.653) are more elastic for labor change than the non-RFID companies (α=0.649) by 0.004, which means the RFID companies with a 1% increase of labor input produced 0.004% more increase in gross income than the non-RFID companies. Thus, even if there is a difference in labor productivity between RFID companies and non-RFID companies, the gap between the two is not significant.

Fig. 2 presents graphical representation of ln(GI) of non-RFID companies and RFID companies with two input values of EMP-WH and FA. These graphs are based on FEM4. The last graph shows the difference of ln(GI) values between non-RFID companies and RFID companies.

6. Discussion

The RFID companies are big companies in the U.S. retail industry. Based on sales of 122 retail companies in 2013, there are eight RFID companies out of the top ten retailers and 14 RFID companies out of the top 20 retailers. There are only three RFID companies in the bottom 50% of 122 retailers. This assures that SMEs are reluctant to adopt the RFID technology.

Per employee gross income (PEGI), calculated by GI divided by EMP, is another measure of labor productivity. Table 6 presents annual average numbers of EMP, GI, and PEGI between RFID companies non-RFID companies. Comparing PEGIs of both groups each year, PEGI of RFID group had been greater than that of non-RFID group for the first four years (2007–2010). However, PEGI of non-RFID group had been greater than that of RFID group for the last three years (2011–2013). Comparing the average number of seven years (2007–2013), even if non-RFID companies' number of employees is 1/10 of that of RFID companies, GI/EMP values of the

Table 6
Comparison of per employee GI between RFID and non-RFID companies.

Year	RFID group				Non-RFID group			
	N	EMP[a]	GI[b]	PEGI	N	EMP[a]	GI[b]	PEGI
2007	22	256.6	14,133.7	$55,073.4	100	19.7	1083.9	$55,096.0
2008	22	254.2	14,553.8	$57,252.8	100	19.8	1100.7	$55,495.4
2009	23	243.7	14,270.0	$58,558.6	99	20.5	1154.3	$56,427.9
2010	24	234.8	14,138.5	$60,228.5	98	21.8	1265.1	$57,916.5
2011	24	240.4	14,484.8	$60,257.6	98	23.0	1412.6	$61,471.9
2012	24	234.2	14,646.5	$62,545.4	98	24.3	1560.4	$64,088.0
2013	25	224.6	14,109.2	$62,806.8	97	26.1	1684.7	$64,583.8
Average		241.2	14,333.8	$59,531.9		22.2	1323.1	$59,297.1

[a] Thousand employees.
[b] Million dollars.

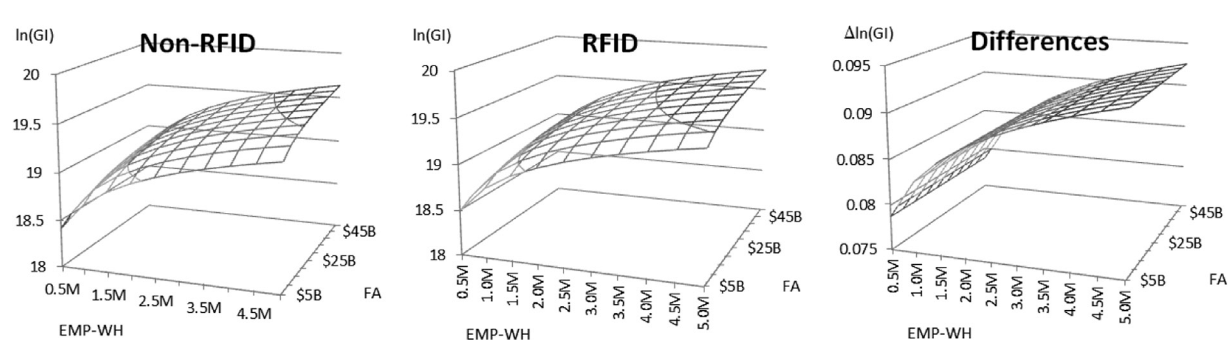

Fig. 2. Comparison of *ln*(GI) between non-RFID and RFID Companies.

two groups are very close. This phenomenon explains why the value of γ in the result of the regression analysis is so small.

There is an ongoing debate about investment in information technology (IT) and benefits from it. As mentioned earlier, the investment in IT does not guarantee financial success, and the productivity benefit from the IT project does not show up immediately (Carr, 2003). Challenges for huge IT projects always go with uncertainty about productivity benefit. The benefit from large IT investments comes with a time lag, and quantifying the financial returns from the IT investment is hard to achieve (Dehning and Richardson, 2002). Electronic Medical Records (EMR) has been a hot issue in the healthcare industry for the last decade. It has been expected to reduce medical expense and to increase productivity in the U.S. healthcare industry. However, some empirical studies show that EMR led to greater health spending and lower productivity. Other studies present that there is no EMR savings to offset the adoption cost (Dranove et al., 2012). The adoption of EMR is progressing slowly, at least, in the smaller practices (Gans et al., 2005). According to Jha et al. (2010), the share of hospitals that had adopted EMR was only 11.9% in 2009, and small, rural, and public hospitals are less likely to adopt the EMR system as compared to larger, urban, and private hospitals. Even if in many cases, costs rise after EMR adoption, hospitals in strong IT locations reduce costs sharply after the first year of EMR adoption compared to that of pre-adoption (Dranove et al., 2012). The same story can be applied to the RFID technology investment. The first movers to adopt the RFID technology in the retail industry were big retailers and the adoption rate has been slowing down since 2007. As Whitaker et al. (2007) states, a successful RFID project depends on whether or not the RFID company has a well-functioning ERP system. Because the RFID project is not just building an independent IT system, it might have little chance to become successful without skilled IT staff and a robust existing IT system. RFID companies' productivity gains should be explained with RFID investment as well as integration effort between the existing information systems and RFID. In addition, the supply chain partners' ability to integrate RFID systems can also be a successful factor of RFID technology investment. Therefore, benefits of RFID technology adoption start with big, IT savvy retailers and it will spread over to the retail industry over time.

7. Conclusions

Since Walmart's announcement of RFID technology adoption in 2003, RFID technology has received a spotlight in the U.S. retail industry. Its adoption boom was in 2005 and 2006 by big retail companies and after 2007, the number of retail companies with RFID adoption has slowed down because of uncertainty of return on investment and the financial crisis in the U.S. economy during 2007–2008 (Shin and Eksioglu, 2014a). The Cobb–Douglas production function suggests, using U.S. retail industry data, that RFID companies have a higher elasticity of labor to gross income than the non-RFID companies, which indicates why RFID companies have higher labor productivity. But the gap between RFID and non-RFID is only 0.004% which is not significant considering the huge amount of RFID technology investment.

Fosso Wamba (2011) argues that RFID technology will appear as an interactive innovation like telephone, Internet, and E-commerce. Collins et al. (2010) assert that RFID technology is a disruptive technology to transform supply chain into a more efficient system. Based on the EUJRC report (EUJRC, 2007), RFID technology will enable total factor productivity gain through business process efficiency. The effect of disruptive technology or interactive innovation does not show up immediately. The total factor productivity is a long-term based concept. If this study expands beyond the 2013 data, it is expected to demonstrate more clearly the effects of RFID technology adoption in the retail supply chain network.

There are some limitations in this paper. First, the output measure in retail industry should be value-added income. However, it is not easy to calculate the value-added income, e.g., a free one year warranty is a value-added feature. Retail industry's service improvement by RFID adoption is hard to capture with financial statement data. In this paper, gross income is used for retail output proxy, which estimates a little higher labor productivity than value-added income in the retail industry. The second limitation is the economies of scale effect for RFID adoption companies. Lee and Lee (2010) mention that there is a cost advantage for RFID technology adoption due to the size of the company. The third limitation is that because RFID investment relates to IT investment, introduction of the number of IT employees and the amount of IT investment could enhance the production function regression in this paper. In addition, as mentioned earlier, Whitaker et al. (2007) argue that existing information systems like ERP is a pre-requisite for the success of RFID project. RFID companies productivity gains should be explained by RFID investment as well as integration effort between the existing information systems and RFID.

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