For WISE 2009

Does IT Really Reduce Inventory?

Opening up the Black Box between IT and Inventory

Richard Lai,* **Sean Xu****, and **Kevin Zhu*****

* The Wharton School, University of Pennsylvania

** School of Business & Management, Hong Kong Univ. of Science & Technology

*** The Rady School of Management, University of California, San Diego

Contact email: kxzhu@ucsd.edu

Word count: 7179

September 2009

Preliminary; please do not cite

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Abstract

This study looks at whether IT reduces inventory, as a specialization of a more general question how IT increases productivity at the firm level. Theoretical literature is ambiguous; the empirical literature, while generally supporting the "distortion-reducing effect" of IT, raises several estimation issues. Based on a large dataset of 1052 firms over 7 years, we examine the IT-inventory relationship by using different measures of IT to account for omitted complementarity bias, adopting recently reported controls to account for omitted variable bias, and employing novel instrumental variables to address possible endogeneity. Surprisingly, our estimation overturns previous results: we find no evidence that IT has any observable effect on inventory. Further probing into the moderators and mediators reveals more subtle roles of how IT really affects inventory. The aggregate IT effect masks differentials across the supply chain. We find that the IT effect is negative among manufacturers, but positive among retailers. Moreover, once we include growth into the inventory regression, the signs on the IT variables reverse. There results run counter to the current consensus, but shed new light on the bigger question how IT increases firm productivity.

Key words: IT productivity, firm performance, inventory, supply chain, empirical research, econometrics, instrumental variables

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1. Introduction

One of the most critical questions about information technology (IT) is whether it enhances productivity. On this issue, there have been great strides in empirically confirming that IT does lead to productivity increases—*e.g.*, the reviews in Brynjolfsson and Hitt (1996), Dedrick, *et al.* (2003), and Banker, *et al.* (2006).

The next big question, naturally, is how IT increases productivity.

In this paper, we focus on a specific mechanism through which IT could enhance productivity at the firm level, by reducing a critical form of working capital: inventory. Inventory is a central subject of study in operations management and it arises as working capital because of mismatches in supply and demand (Cachon and Terwiesch (2006)). Its importance is evident: it comprises 20% of total assets for the average listed firm in the period from 1997 through 2006 (Lai (2006)).

So we ask: does IT really reduce inventory at the firm level?

Our answer is a surprising "no." This is surprising because evidence in the extant literature suggests that IT reduces inventory (*e.g.*, Mukhopadhyay, *et al.* (1995), Barua, *et al.* (1995), Zhu and Kraemer (2002)). We depart from the literature by addressing important estimation issues. In particular, we adopt instrumental variables (e.g., executives' college majors and age, and the number of transistors on microchips) to address likely endogeneity issues that otherwise may affect the results. This renders new evidence suggesting an insignificant relationship between IT and inventory. From a theoretical perspective, the new evidence is intriguing given its deviation from the widely recognized notions that IT can help improve information flows along supply chains (*e.g.*, Lee (2004)), which, in turn, should increase efficiencies in inventory management (*e.g.*, Ketzenberg, *et al.* (2007), Milgrom and Roberts (1988)).

We are thus motivated to probe deeper into moderating and mediating effects on the IT-inventory relationship. In so doing, we find that IT does affect inventory, but in more subtle ways than previously thought. Specifically, IT *reduces* inventory for manufacturers, but *increases* inventory for retailers. The former finding is consistent with theory that IT reduces inventory by reducing information distortion (let's call it the *distortion-reducing effect*); information distortion is found greater among manufacturers in upstream supply chains (Lee, *et al.* (1997)). Yet, the latter finding (IT increases inventory for retailers) is somewhat surprising, but it is consistent with theory that IT is also a strategic platform for growth, which in turn may increase inventory (Mitra (2005)). For manufacturers, this growth effect seems to be dominated by the distortion-reducing effect. For retailers, the growth effect dominates instead. Together these findings add to the literature by opening up the "black box" between IT and inventory.

The rest of this paper provides details. In section 2, we review the literature and building upon that literature, we posit three hypotheses. In section 3, we describe our dataset and empirical approach; in section 4, the baseline results; in section 5, robustness tests; and in sections 6 and 7, moderator and mediator effects. Section 8 concludes.

2. Literature Review and Hypothesis Development

We first review the empirical literature. The point is that the literature raises important but unresolved empirical issues. We next review the theoretical literature. Here, the theme is that theory is conflicted about whether IT reduces inventory. Therefore, our study is motivated by both the unresolved empirics and the conflicting theories. Drawing upon the literature, we develop three hypotheses for empirical test before closing this section.

2.1 Empirical Literature

Given the importance of the question on IT and inventory, there have been a number of related empirical studies. For example, Barua, *et al.* (1995) show that IT capital is positively associated with inventory turnover. Mukhopadhyay, *et al.* (1995) find that electronic data interchange

(EDI) is associated with inventory reduction in the auto manufacturing industry. Hitt, *et al*. (2002) reached the same conclusion with enterprise resource planning (ERP), and so did Zhu and Kraemer (2002) with Internet-based e-commerce technologies. These prior studies largely support the notion that IT reduces inventory.

But these studies raise additional issues. First, the effect of specific technologies like EDI, ERP or e-commerce might be confounded by that of other technologies. Zhu (2004) suggests that inventory is influenced not only by specific technologies, but also by significant complementarities among them. As a hypothetical example, e-commerce investments might be observed to correlate with low inventory only because of unobserved accompanying investments in IT infrastructure, without which e-commerce investments would actually have a lower impact on inventory. Without accounting for the full suite of technologies and their complex interactions, an estimation using specific technologies would suffer from potential *omitted complementarities bias*.

Another issue is that there may be other variables that affect inventory. Many of these are reported only in the recent literature (*e.g.*, Gaur, *et al.* (2005), Rumyantsev and Netessine (2007)), prior to the studies mentioned above. Estimations that exclude the variables that correlate with IT run the risk of *omitted variables bias*. While this bias is econometrically similar to the omitted complementarities bias, its origin is different. It involves variables that might correlate with IT in its impact on inventory, rather than variables that directly interact with IT.

A third issue is potential *endogeneity*. This could arise in two ways. Inventory and IT could be jointly determined by other factors. For example, competition might simultaneously drive up investments in IT as well as split demand, which in turn—through the classical newsvendor formulation (Porteus (2002))—reduces inventory. So the relationship between IT and inventory could be spurious. Another possibility is reverse causality. For example, reduced inventory might improve profitability, which provides funds for firms to invest more in IT.

In this paper, we seek to address these three issues by building upon and extending the existing literature.

2.2 Theoretical Literature

Given the three unresolved empirical issues identified above, we turn to theoretical literature for guidance. But we soon discover that theory is conflicted, with one view suggesting that IT reduces inventory and another suggesting the opposite. Our research question is on the directional impact of IT on inventory. This includes if inventory might have a reverse directional impact on IT or if there are third factors that jointly determine both IT and inventory. These latter effects may well exist, and it is the job of our empirics to partial them out and identify if there is still any remaining impact of IT on inventory.

2.2.1 *IT reduces inventory?*

In one view, IT reduces inventory because it reduces information distortion both within firms and between firms in a supply chain—*e.g.*, Ketzenberg, *et al.* (2007), Milgrom and Roberts (1988). A well-known mechanism is that increased information transparency reduces lead time, improves demand forecasts and reduces uncertainty, which in turn reduces safety stock, pipeline and cycle inventory (Lee, *et al.* (1997)). For example, a case study on a large high-tech manufacturer offers support that ERP applications standardize and increase visibility of operational data (*e.g.*, production and inventory) among the firm's three distribution centers, thereby significantly reducing lead time in order fulfillment (Cotteleer and Bendoly (2006)). A large literature has emerged seeking to demonstrate, at least in theoretical models, that information sharing can reduce inventory (*e.g.,* Cachon and Fisher (2000), Johnson and Whang (2002)). For example, Cachon and Fisher (2000) use simulations to estimate that information sharing between firms can lower "supply chain costs" (mostly related to inventory) by 2.2%. Meanwhile, there is also research on how the disruption of information sharing can lead to higher inventory (*e.g.,* Hendricks and Singhal (2003)).

Another mechanism is that IT reduces errors that can lead to higher inventory. For example, a filed study on a Fortune 500 supplier and its customers suggests that IT applications in business-to-business (B2B) procurement processes are critical in terms of decreasing order conflicts, *e.g.*, wrong part code or an obsolete part (Mukhopadhyay and Kekre (2002)). Hitt, *et al.*

(2002) also emphasize that ERP applications allow a firm's order-capturing process to automatically update its production plans and inventory stock levels; such process automation reduces human intervention and possible errors in production and inventory management.

Still there are other variants of the "IT reduces inventory" theory. For example, IT might reduce inventory only after a lag, much as it does in its impact on general productivity (Brynjolfsson and Hitt (1996)). If so, we might even observe that IT is associated with *higher* contemporaneous inventory levels, as firms invest in IT to curb excessive inventory. But still, the prediction is that IT reduces inventory, even after a lag.

2.2.2 *IT increases inventory?*

There are several theories about how IT might even *increase* inventory. One theory arises from the view that the dominant role of IT is strategic: IT is an enabler of growth because a growing firm can leverage IT to coordinate its operations which become more complicated (Mitra (2005)). This is consistent with the argument that IT investments in general and ERP applications in specific provide additional headroom to support growth in business volumes (Anderson, *et al.* (2006)). It is also known that sales growth leads to more inventory, in a direct way as formalized in classical inventory management models (Porteus (2002)) or indirectly, via increased product variety (Randall, *et al.* (2003)). Therefore, we could observe that IT leads to increased inventory.

A related notion emphasizes IT's ability to help firms better manage product variety and business complexity in general (Gao and Hitt (2004), Milgrom and Roberts (1995)). Further, Fisher and Ittner (1999) argue that product variety increases inventory levels. Putting these together, IT investments could lead to higher inventory, possibly mediated by product variety.

Brynjolfsson (1993, p.75) argues that "the rapid speedup enabled by IT can create unanticipated bottlenecks at each human in the information processing chain." Such perverse effects of IT could reduce management monitoring that keeps a lid on inventory management (Lai (2008)). This can form another pathway through which IT might increase inventory.

2.3 Hypotheses

Our research question is to ask which of the two views—"IT increases inventory" or "IT reduces inventory"—dominate, even if both might be simultaneously at work. We shall call this dominant effect of IT on inventory the "*IT effect*." In recognition of evidence in prior studies (as reviewed above) about IT's negative impact on inventory, we formulate our baseline as a one-sided hypothesis to make it testable:

H1: IT has a negative effect on inventory for the average firm.

The theoretical literature also suggests that the IT effect works through specific mechanisms, two of which are particularly prominent. The first is the distortion-reducing role of IT, in which IT reduces inventory by reducing information distortion within and between firms. Since distortion is greater in upstream activities based on the well-known "bullwhip effect" (Lee, *et al.* (1997)), this theory suggests two natural "moderator" hypotheses:

H2a: The IT effect is moderated by a firm's position in the supply chain. Specifically, it is smaller in upstream supply chain (e.g., for manufacturers) than in downstream supply chain (e.g., for retailers).

H2b: The IT effect is moderated by the type of inventory within a firm. Specifically, it is smaller for raw material inventory than for finished goods inventory.

Although "smaller" and "more negative" could be used in the above hypotheses, we use the former to emphasize that the net IT effect may not be negative. When it is negative, "smaller" means more negative (that is, "stronger"). The theoretical prediction is only that the distortion-reducing role of IT is stronger upstream, *ceteris paribus*, but there is no prediction that the net IT effect is negative, whether upstream or downstream.

The second mechanism is mediation through firm growth, in which IT leads to growth, which in turn leads to higher inventory:

H3: A positive IT effect is mediated by firm growth. Specifically, IT leads to greater firm growth, which in turn would lead to higher inventory.

We formulate *H3* as conditional on observing a positive IT effect. Conceptually, IT could increase inventory via growth even when the IT effect—which is a *net* effect—is negative. But of course, there is no identification strategy to link growth to IT's increasing inventory, so an unconditional hypothesis, while conceptually correct, is not empirically testable.

To summarize, *H2a*, *H2b*, and *H3* go beyond the baseline *H1 to* provide insights into the mechanisms how the IT effect works, by examining its moderators and mediators. Figure 1 summarizes our hypotheses.

------ Insert Figure 1 about here ------

3. Data and Methodology

We first describe the specification to test our baseline *H1*, and then address how we test *H2a*, *H2b*, and *H3*. To test *H1*, we use the following reduced form:

(1) $$\iota_{it} = \sum_{y=t-l}^{t} \tau_{iy} + \Delta_{it} + \phi_i + \psi_t + \varepsilon_{it}$$

where ι_{it} is a measure of inventory and *i* and *t* index firm and year, respectively. τ is IT, the variable of interest, with up to *l* lags. Δ is a vector of control variables that can affect inventory. Unless otherwise stated below, we use log specifications for all variables to facilitate interpretation of the results and to account for possible non-linearities. ϕ captures firm effects and ψ, year effects. ε is assumed to be white noise. We bear in mind that time-invariant firm characteristics, such as industry classification, are absorbed into ϕ, while time-correlated characteristics such as macroeconomic trends and firm age are absorbed into ψ. All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term.

To estimate model (1), we use data from several sources. From the *Computer Intelligence* (CI) database, we obtain proprietary information on firms' IT infrastructure and applications. From *Information Week*, we obtain rankings of firms' use of IT, as an additional measure of IT. We use *Compustat* for information about financial statements, such as various types of inventory on the balance sheet. We obtain executives' year of birth and college majors and their other details from *CapitalIQ*. We use still other sources for specific information, such as historical issues of PC Magazine, the Federal Reserve Secondary Market TBSM series, and the Bureau of Labor Statistics. These are discussed below. We use GVKEY to establish concordance among these datasets. In some cases, such as the CI and Information Week datasets, we have to manually code the GVKEYs for the observations based on their company identity information (*e.g.*, name, industry sector, location, website, stock market ticker, etc.).

Our resulting dataset is a panel from 2001 through 2006, for manufacturing, wholesale, and retail firms (NAICS codes 31-46). We exclude firms with non-positive net sales, cost of goods sold (COGS), inventory, and accounts payable. There are 8,615 unique firms in the panel, although only 1,052 have inventory and IT values for our baseline estimations. We use the rest to test if these 1,052 might have sample selection bias.

Table 1 summarizes both the 8,615 unique firms—which we call the *universe set*—and the 1,052 unique firms—which we call the *estimation set*. Table 1 first presents measures for inventory. We obtain inventory level (raw materials, work-in-progress, finished goods, and total) from Compustat. In our baseline estimation, we use total inventory (in days), defined as inventory—adjusted with LIFO reserves—divided by COGS/365. We describe alternative measures in the section on robustness tests.

------ Insert Table 1 about here ------

Next, we discuss the measures for IT, firm characteristics as control variables for inventory, and the instrumental variables (IVs). These three discussions also speak to how our approach departs from the literature, by addressing the three empirical issues mentioned in the literature review—*i.e.*, omitted complementarities, omitted variables, and possible endogeneity.

3.1 IT Measures to Address Omitted Complementarities

Recall that the issue of omitted complementarities arises because it is difficult to accurately estimate the impact of narrowly defined technologies (Weill and Broadbent (1998), Zhu (2004)).

For example, a relatively functional technology such as ERP or supply chain software might have some impact on inventory, but this impact also depends on other IT investments. Further, these other IT investments could have their own impact on inventory. Indeed, some of these might be general technologies like electronic mail (see the Milgrom and Roberts (1988) theory of inventory and communications as substitutes), and still others are investments like user training, and are not typically captured by IT variables used in prior research.

In light of such complex complementarities among a diversity of IT investments, our approach is to attempt to capture as much of IT as possible, using both broad and narrow measures, and to explicitly account for their interactions. Table 1 shows these measures.

3.1.1 *Variables from Computer Intelligence*

From the CI (or Harte Hanks) database, we obtain measures of IT stock, IT labor, as well as firms' usage of enterprise resources planning (ERP) applications. The database contains detailed information about IT hardware (*e.g.*, servers and personal computers), software applications (*e.g.*, ERP), and IT labor at the establishment level. We aggregate the information to the firm level.

We define a firm's "IT stock" as the replacement value of IT hardware as proxied by servers and personal computers. This is consistent with the measure of IT stock used extensively in the IT literature (e.g., Hitt and Brynjolfsson (1996)). The literature suggests that the depletion period for computer capital is about three years (Gurbaxani, et al. (2000)). As such, the replacement value of computer equipment in year *t* is estimated as follows:

(2)
$$(P_t + \frac{2P_{t-1}}{3} + \frac{P_{t-2}}{3})\frac{Q_t}{3},$$

where P_t is the market price of computers in year *t* and Q_t is the number of computers. This formulation, following the standard literature, is practical, consistent, and somewhat robust (*e.g.*, Hitt and Brynjolfsson (1996)). We apply this formulation to both personal computers and servers. We obtain historical prices of personal computers from *PC Magazine* and, following recent research using the CI database (e.g., Gu, *et al*. (2008)), estimate servers' price to be five times that of personal computers. The extent to which the distribution of personal computers and servers varies between firms is mitigated by our use of firm, industry, and year effects to capture unobserved heterogeneity. We also divide IT capital by total assets for size adjustment.

"IT labor" is the product of the number of IT employees and IT wages from the *Bureau of Labor Statistics*, scaled by total assets. This serves as a proxy for both software investments and other labor-correlated expenditure, such as labor itself, training, and supervision (Hitt and Brynjolfsson (1996)).

Regarding ERP applications, we obtain two types of indicator variables from the CI database, one for whether an establishment uses general ERP and another for whether it uses more specialized supply chain ERP. For each type, we construct three firm-level ERP usage scores by aggregating a firm's establishment-level indicator variables: (1) simple averaging, (2) averaging using establishment employees as weights, and (3) averaging using establishment revenues as weights. We also use two other variables that are more continuous than dichotomous indicators: the percent of a firm's employees who are supply chain ERP users and the percent who are general ERP users.

3.1.2 *Variables from InformationWeek rankings*

While IT stock and labor objectively capture cumulative IT investments, they suffer from managerial discretion in how the investments are depreciated and whether they are expensed or capitalized. Also, IT stock might unnecessarily include poorly implemented IT and unnecessarily exclude IT-related spending beyond that directly incurred by IT departments, such as user training and managerial time. InformationWeek's annual ranking of firms could address these shortcomings. According to InformationWeek, their ranking goes beyond IT "spending plans and budgets" and encompasses items such as "end-user training" and "middle management support." The ranking also considers how "effective" and "innovative" are IT investments. Hence, this measure is a good complement to the CI measures (IT stock and labor).

The rankings are suitable for our use in other ways as well. First, it is plausible that firms with stronger IT have more incentive to file for ranking, so this biases us toward finding a relationship between IT and inventory and works conservatively against our baseline result. Another advantage is that we have some first-hand knowledge to ascertain that the ranking is reasonably robust. Finally, the ranked firms must have at least $500 million in revenues, so explicit selection criteria make it easy to apply a Heckman correction model. We have annual rankings from 2001 through 2006. We use ordinal ranking (500 through 1, the lowest; unranked firms are assigned 0) and a "ranked in top 500" indicator.

Although we have conceptually many variables to capture IT, we expect that some of these measures may be empirically insignificant. Therefore, we run a first estimation with all variables and their interactions, and to reduce specification error, we run our baseline estimation without the variables that are insignificant in the first estimation.

3.2 Control Variables to Address Omitted Variables Bias

Recall that the issue of omitted variables arises from omitting control variables that affect inventory; many of these are reported only in the recent literature. There are two approaches to deal with this. The first is to construct a measure of inventory that is the residual of a first-stage regression in which inventory is regressed on the control variables. This new measure of inventory should then be regressed on the residuals from a regression of our variables on the same controls. The second approach is to simply include these controls as variables explaining inventory. The two approaches are both unbiased, so we report results using the second approach because it is simpler. Unreported results using the first approach, unsurprisingly, produce the same estimates with smaller standard errors.

We partial out known explanations for firm-level inventory levels reported in two recent papers. Gaur, *et al.* (2005) include: (1) COGS, a proxy for scale, (2) gross margin, defined as the ratio of net revenues less COGS to net revenues, (3) capital intensity, defined as gross property plant and equipment (PPE) divided by gross PPE and LIFO-adjusted inventory, and (4) sales surprise, defined as the ratio of actual to projected sales. Since projected sales is unobserved, we follow the literature and make two kinds of projections, based on four-quarter moving averages and on Holt-Winters' exponential smoothing method. The latter formulation is:

(3) $$SALES\_FORECAST_{ft} = L_{f,t-1} + T_{f,t-1}\ ,$$

where L and T are smoothed series defined as:

(4) $$L_{ft} = \alpha.SALES_{ft} + (1-\alpha)(L_{f,1-1} + T_{f,t-1})\ , \quad \text{and}$$

(5) $$T_{ft} = \beta(L_{ft} - L_{f,t-1}) + (1-\beta)T_{f,t-1}\ ,$$

in which we set the weights α and β to 0.75, again following the literature (i.e., Gaur, *et al.* (2005)). The initial values are obtained by fitting a linear regression with a time trend using the first half of the observations in the dataset. We make no out-of-sample forecasts. We adopt a scale control in robustness estimation as in Gaur, *et al.* (2005).

Rumyantsev and Netessine (2007) use a different set of variables, based on "classical models" of inventory management. These are: (1) size (measured by COGS), (2) gross margin, (3) lead time (based on a model of the cash conversion cycle), (4) "sigma sales" (described below), a measure of demand volatility, (5) growth, (6) interest rate (the 3-month Treasury rate, from the Federal Reserve Secondary Market TBSM series, in which we take the geometric mean of monthly rates), and (7) sales surprise (sales divided by forecasted sales, where we forecast using several methods, such as Holt-Winter and four-period moving average). Sigma sales is the moving variance of sales X in:

(6) $$\sqrt{\frac{\sum_{i=0}^{3}\left(X_{t-i} - \sum_{j=0}^{3} X_{t-j}/4\right)^2}{4}}$$

where we obtain sigma sales for the first three years by linear backward extrapolation.

Table 1 shows these variables, as well as others used in our estimation.

3.3 Instrumental Variables (IVs) to Address Endogeneity

Our contention is that measures of IT are likely to be endogenous, so we first need to confirm that. Following Hausman (1978), this involves first getting the residuals from a regression of IT on all variables in equation (1) with the instrumental variables (IVs), and then estimating (1) with the residuals on the right hand side and test for their coefficients.

Since we suspect that complementarities are important, we might have many significant interaction variables in our specification. Therefore, we construct six IVs to ensure that we satisfy the rank and order conditions in IV estimation.

We construct four IVs using a dataset from *CapitalIQ*: the average year of birth and the percent of executives who have college majors in IT, quantitative disciplines, and the arts. An "executive" is defined as in regulatory filings, as a corporate officer or director—*i.e.,* one who has authority to contract on behalf of the firm (Knepper and Bailey (1998)). This approximates the "C-level" titles (such as CEO, CFO) used in popular parlance.

For IT majors, we search using the key "inform* or tech* or comput* or web* or internet*." For quantitative disciplines, we count 18 disciplines; for arts, we count 17. The search keys for these are obtained by manually inspecting all 926 majors in our dataset of 2,904 executives, so these keys are really partitioning criteria.

Not surprisingly (and econometrically required), the three college majors IVs are correlated, but they are not an affine function because we have still many other majors not included, such as architecture, design and medicine. For example, the correlation of the percent of executives with IT majors with that for quantitative majors is -0.019, and with that for arts majors is 0.368. We also bear in mind that the construction of these instruments need not be precise, since the identification requirements are that they are correlated with IT and are exogenous with inventory.

For the fifth IV, we use the transistor count on the most popular personal computer chip in the year, which we obtain from Wikipedia. This count is plausibly exogenous to firm-specific factors that might affect inventory, except through the desired channel of IT. Because this IV is invariant across firms, its identification is only incremental to the first four IVs.

As a sixth and final IV, we use the lagged dependent variable (*i.e.,* inventory), as in Arellano and Bond (1991).

Table 1 summarizes the first four IVs.

Our use of executive characteristics as IVs is core to our empirical strategy, so we verify their suitability along four dimensions: correlation with endogenous IT, exogeneity to the dependent variable, disclosure bias, and within-firm invariance. The results confirm the validity of the IVs.

3.4 Testing Moderator and Mediator Effects under *H2a, H2b, H3*

We use a standard *seemingly unrelated estimation* (SUE) to test the moderator effects under *H2a* and *H2b*. This exploits all information in a system of equations (*e.g.,* one for manufacturing and one for retail under *H2a*, or one for raw materials and another for finished goods inventory under *H2b*). We test for the equality of the coefficients for the IT variables across the equations. *H2a* is also amenable to a different approach; that is, we interact the IT variables with the moderator, which is a supply-chain-position variable, coded 3 for upstream manufacturers (NAICS 31 through 33), 2 for wholesalers (32), and 1 for downstream retailers. Identification with IVs carries through in a straightforward way, by interacting the IVs with the supply-chain-position variable. However, this latter approach restricts estimates of the explanatory variables to be equal in all equations (*e.g.,* the coefficient for COGS is the same for manufacturers and retailers), so we consider this approach as a robustness test, and use the SUE as our baseline estimation.

The test for mediator effects in *H3* is more complex. We follow Baron and Kenny (1986) and test firm growth as a mediator by first running two estimations: a “growth regression” which establishes that inventory correlates with growth, and a structural equation which is equation (1) with growth as an additional variable. The explanatory variables for firm growth are well-known (*e.g.*, Lang, *et al.* (1996)), and we include COGS, gross margin, and gross PPE. We also include others, such as debt leverage, cash flow on assets, and book-to-market ratio, but find that these are statistically insignificant with firm fixed effects, so we exclude these to improve our specification. From the growth regression and the structural equation, we construct the Aroian *Z* statistic to summarize the presence of mediation because it does not need to assume that the multiple of the standard errors from the two estimations is vanishingly small.

4. Baseline Results

In Table 2, we report our baseline results. In columns (A) and (B), we show that our IT measures can replicate results in previous studies. In these examples, the estimates using either a narrow measure of IT (use of general ERP at a firm, as a simple average of establishments' use) or a broad one (IT stock and labor) are negative. Since we use logs for continuous variables throughout this study, the interpretation is that 1% increase in the ERP score or in IT stock is associated with 0.07% or 0.032% decrease in inventory, respectively. The coefficient on IT labor is negative too, though it is not statistically significant. Nevertheless, a joint test of both IT stock and labor produces a significant F statistic of 13.68.

We next estimate the IT effect using the full set of narrow and broad IT variables with one year lags and the control variables from Gaur, *et al.* (2005). The full set of IT variables includes:

- 12 first-level variables: IT stock, IT labor, the 3 supply chain ERP scores, the 3 general ERP scores, percent of employees who are users of supply chain ERP and likewise for general ERP, InformationWeek rank, and the InformationWeek "ranked" indicator; and
- 66 interaction variables, representing two-way interactions of the 12 first-level variables.

In column (C), we report estimates of 15 of the 78 (=12+66) IT variables that are statistically significant. For parsimony, we call these the "15 complementarities." The significance of these 15 variables and the significance of the Gaur, *et al*. (2005) control variables point to omitted complementarity and omitted variable biases if these were excluded in the specification. Reassuringly, the control variables are signed as in Gaur, *et al.* (2005). If we were to stop here, we would conclude that "IT reduces inventory."

------ Insert Table 2 about here ------

In column (D), we introduce the IVs, using two-stage-least-squares (2SLS). We also employ the standard approach to data reduction (Stock and Watson (2002)) to address the high dimensionality of the 15 complementarities, which are collectively difficult to sign, since they individually have different signs and different significance levels. Following Peres-Neto (2005), we first undertake a Bartlett's test, which produces a significant result (p=0.000, χ^2=52380). This then leads us to use their optimal stopping rule (which they called the Avg-PA) of using the first two principal components.

Now, in the column, we see that even statistical significance disappears, for both components singly (and in a joint test, jointly too). In unreported estimations, we also carry out the IV analysis to regress inventory on the 15 complementarities as shown in column (C); we use the interactions of the IVs to meet the rank and order conditions. None of the 15 complementarities are statistically significant; they are also jointly indistinguishable from zero (F=0.94, p=0.520). When we use the Rumyantsev and Netessine (2007) control variables, the principal components are again jointly insignificant (p=1.413, F=1.04).

Taken together, columns (C) through (D) confirm that the impact of IT is subject to biased estimation without accounting for complementarities, omitted variables, and endogeneity. In particular, the most intriguing result is that we find no evidence to support *H1*.

We also conduct a number of tests to check the validity of the IV analysis. First, a Hausman test suggests endogeneity of IT, whether we use the 15 complementarities (p=0.000, F=4.41) or the 4 principal components (p=0.033, F=2.64). Second, all IVs pass the identification test of exclusion restriction, confirming the IVs' correlation with IT. Finally, we undertake the three tests for IVs' exogeneity to inventory. The results are in Table 3. Recall that our first test is to directly check if increased inventory leads to higher IVs. Columns (A) and (B) show the results for two example IVs: inventory and its lagged value—either singly or jointly—do not lead to a higher average year of birth among firms' executives or to a higher percentage of executives with IT majors. Similar tests confirm exogeneity of other IVs. The second test restricts the sample to firms with only inventory decreases. Column (C) replicates the baseline IV estimations in column (D) of Table 2, but with this restricted sample and a correction for potential sample selection bias. We see that, as in the baseline results, the principal components are indistinguishable from zero, either singly or jointly. Our third test for over-identifying restrictions also provides support for exogeneity. For example, we cannot reject exogeneity of the IVs with respect to IT when it is measured using the principal components (p=0.116).

Taken together, the above results suggest that the IVs are valid. So our baseline result stands: *H1* is not supported and there is no statistically-significant evidence that IT reduces inventory.

------ Insert Table 3 about here ------

Robustness of Results

We bolster the baseline results with a battery of robustness tests by using (1) alternative measures of inventory, (2) alternative measures of IT, (3) alternative IVs, and (4) correction for potential selection bias. We undertake the complete combination of variations described below—*i.e.,* alternative measures of inventory with alternative measures of IT with alternative controls, with and without log specifications, with and without treatments for outliers, etc. To stay within page limit, these results are not reported here but are available upon request.

5. Moderator Test Results (*H2a*, *H2b*)

The moderator hypotheses *H2a* and *H2b* predict that we are more likely to observe stronger IT effects upstream (manufacturers versus retailers, raw materials versus finished goods). If so, the results would be consistent with a theory in which IT works through the mechanism of mitigating information distortion to reduce inventory.

Table 4 presents results of testing *H2a* and *H2b*. In columns (A), (B), and (C), we run the SUE—described in Section 3.4—in a system of equations for manufacturers, wholesalers, and retailers. We also show an example of our robustness tests, using variables from Netessine and Rudi (2006) for controls. IT, measured with the 4 principal components, is now significant for manufacturers and retailers. The evidence is consistent with the prediction of *H2a*. First, the most important first and second components—which by themselves capture about half of the variance—are smaller for manufacturers than for wholesalers, whose first two components are in turn smaller than those for retailers (which are intriguingly even positive). Second, for manufacturers, the combined magnitudes of the first two components are larger than the combined magnitudes of the last two. Third, for manufacturers and retailers, one-sided joint tests for their respective positive and negative signs are significant at the 0.000 level, as shown in Table 4. Fourth, a generalized Hausman (1978) cross-equation test shows that *all* components are smaller for manufacturers than for retailers (χ^2=114 and p=0.000). Taken together, we interpret these as evidence that supports the prediction of *H2a*.

We next turn from tests of the IT effect *between* firms to that *within* firms. Columns (D), (E), and (F) report tests of the IT effect on different types of inventory (raw material, WIP, and finished goods). However, the estimates about IT effect are not statistically significant, either singly or jointly. Nevertheless, consistent with *H2b*, the IT estimates are generally smaller for raw materials than for finished goods. Formal Hausman cross-model tests confirm these (χ^2=6604, p=0.000; χ^2=6180, p=0.000, respectively), although there is no size ordering between raw materials and WIP. We interpret this as only weak, if any, evidence to support *H2b*.

Taken together, these results provide intriguing insights into the effect of IT on inventory. *Ex ante*, theory is silent on whether the *opportunity* to reduce the greater information distortion between firms is overwhelmed by the greater *difficulty* of applying IT between firms. Our result is consistent with an explanation in which opportunity exceeds difficulty, so that we observe that the distortion-reducing role of IT is more evident between firms.

------ Insert Table 4 about here ------

This explanation leads to an additional test on the moderator role of *product market uncertainty*, because the greater the product market uncertainty, the greater the information distortion and order variability along the supply chain (Lee, *et al*. (1997)). In such an environment, IT should have a salient distortion-reducing effect. The results (available upon request) confirm that the IT variables have negative coefficients on inventory when product market uncertainty is high. Overall, this additional test offers complementary support that IT can reduce inventory by mitigating information distortion (especially when uncertainty is high).

6. Mediator Test Results (*H3*)

H3 posits that IT affects inventory via firm growth as a mediator. One complication is that the standard Baron and Kenny (1986) test checks if a significant positive IT effect is reduced when growth is included in the specification, but our baseline result is that the IT effect is *not* significant. There are two remedies. The first is to estimate only in cases where the IT effect is significant. In particular, we can exploit the significantly positive IT effect among retailers. For robustness, we can correct for potential sample bias in this restriction to retailers. The second approach is to do estimate for cases where the IT effect is negative (*e.g.,* manufacturers) or insignificant (*e.g.,* wholesalers, or even the entire population). Although the standard test is not meant for such samples, a simple test of whether the IT effect is reduced provides additional assurance for the main estimation with retailers.

We use six measures of growth: growth in COGS, in sales, and in assets, and the log versions of each of these. As described in the previous section on robustness, we estimate with other permutations, such as different IT measures and control variables. In Table 5, we show the estimations using the principal components to measure IT, asset growth to measure firm growth, and the Gaur, *et al.* (2005) variables for controls in addition to the usual year and industry controls.

Column (A) is the growth regression. Consistent with *H3*, the major components of IT (the first two) are positively correlated with growth. A joint test that all 4 IT components are positively correlated is significant at the 0.000 level.

Column (B) is the inventory regression with growth now included. Consistent with *H3*, the growth variable is positively signed and statistically significant (at 1% level). Interestingly, the signs on IT components are now dominated by the larger, negative first two components. As the column shows, a joint test that all 4 IT components are negative is significant at the 0.000 level. This is a reversal of the positive IT effect in the baseline for retailers. Including growth makes a material difference.

------ Insert Table 5 about here ------

The key test is Aroian *Z* statistic, which is significant for each of the 4 components, with respective *p* values of 0.00028, 0.00023, 0.00075, and 0.00056. This is robust to a Heckman sample selection correction. Further, tests using the other samples return qualitatively the same result. For example, the *p* values of Aroian Z, when we use the entire population, range from 0.0021 to 0.028. Taken together, we interpret the above as evidence consistent with the prediction of *H3*.

7. Discussion and Conclusion

We begin this study by asking whether IT reduces inventory at the firm level, as a specialization of a more general question of how IT increases firm productivity. Theoretical prediction in the literature is ambiguous about this question: it is not obvious whether the dominant relationship between IT and inventory is negative, positive, or just spurious. We are also motivated by previous empirics: while the literature suggests that IT reduces inventory, it also raises several estimation issues. Based on a large dataset of 8,615 firms over 7 years (1052 firms in the estimation sample), we build on and extend the literature through examining the IT-inventory relationship by using different measures of IT to account for omitted complementarity bias, adopting recently reported controls to account for omitted variable bias, and employing novel instrumental variables to address possible endogeneity.

Surprisingly, our baseline finding overturns previous results: we find no evidence that—for the average firm—IT has any significant effect on inventory. Further probing into the moderators and mediators suggests that the IT effect is much more subtle, with conflicting mechanisms that increase and decrease inventory.

Our moderator tests suggest that the average non-effect of IT masks differentials across the supply chain. The IT effect is *negative* among manufacturers, neutral among wholesalers, and even *positive* among retailers. This is consistent with the theory in which IT decreases inventory by reducing information distortion, which is greatest upstream, among manufacturers. Thus, we find evidence to support IT' *distortion-reducing effect* in that part of the supply chain. Practically, this spells good news for firms (and IT suppliers): it appears that IT has been successfully applied to reduce information distortion. We might even conjecture that, following the Milgrom and Roberts (1988) theory of inventory and communications as substitutes, as IT becomes less costly, it can become increasingly attractive to substitute inventory with IT.

But intriguingly, we do not have strong evidence that IT has this distortion-reducing effect within firms: finished goods inventory does not have a significant negative IT effect as predicted, nor does raw materials inventory have a significant positive effect. This result points to two possibilities. One is that there is less information distortion within firms; the other is that it is more difficult to reduce distortion within firms. The former seems more plausible, but this is a fruitful area for further confirmation.

Our mediator tests indicate that growth is a mediator of the IT-inventory relationship. Our results show that IT is positively associated with growth, which in turn is positively associated with inventory. Interestingly, once we include growth into the inventory regression, the signs on the IT variables become negative (especially the first two IT components). This is a reversal of the positive IT effect in the baseline for retailers, suggesting that including growth makes a difference. In practice, the positive IT-growth linkage could imply that retailers have been particularly successful in using IT as a strategic platform for firm growth. This can be another area for future inquiry. Meanwhile, there could be still other mediators such as product diversification. Future research can investigate what else is mediating the IT-inventory relationship.

This study offers certain managerial implications. First, the role of IT in reducing inventory needs to be understood in the context of the supply chain and the nature of the inventory. The effects are different for upstream and downstream firms, and for raw materials and finished goods inventory. Second, IT may be used strategically to enable growth or diversification. This requires a different way of positioning IT. Wal-Mart is an example of such strategic use of IT.

In conclusion, this paper reports results that run counter to the current consensus, but it reveals more subtle roles of how IT really affects inventory. We hope this helps better understand the bigger question how IT improves firm performance.

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Figure 1—Hypotheses

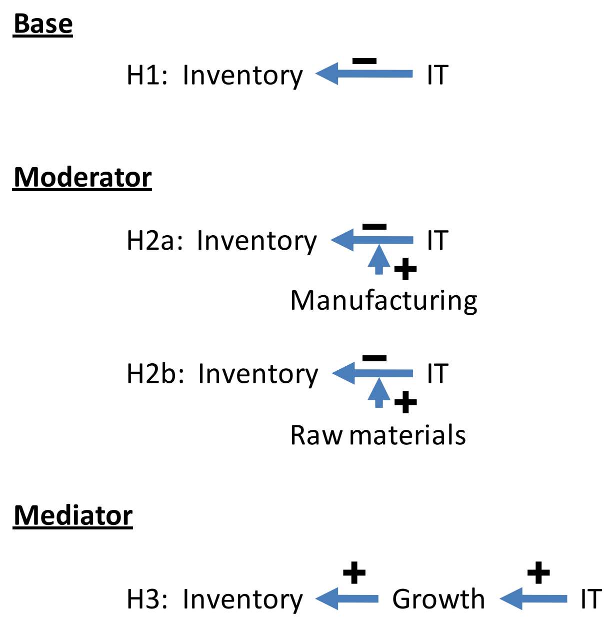

Table 1—Summary Statistics

We combine data from several sources: CI, InformationWeek, Compustat, CapitalIQ, and Federal Reserve Secondary Market TBSM. We use GVKEY to establish concordance among these datasets. We exclude firms with non-positive net sales, cost of goods sold (COGS), inventory, and accounts payable. Our resulting dataset is a panel from 2001 through 2006, for manufacturing, wholesale, and retail firms (NAICS 31 to 46). The whole dataset has 8,615 unique firms and is used for sample selection correction. The core dataset has 1,052 unique firms and is used for estimation. All amounts are in US$ millions (except noted otherwise).

	The universe set			The estimation set		
	N	Mean	SD	N	Mean	SD
Year	48054	2003.5	1.7	4894	2003.4	1.7
INVENTORY						
Inventory level, total	16055	381.9	1433.6	4894	595.5	1752.8
• Raw materials	10753	75.0	242.1	3342	96.3	183.4
• WIP	10302	70.3	360.3	3099	92.5	274.7
• Finished goods	10698	162.0	705.7	3349	213.0	590.3
Days of inventory, total	16035	149.4	1249.7	4894	91.4	102.6
• Raw materials	10738	52.6	247.9	3342	31.0	28.5
• WIP	10288	38.1	701.0	3099	22.7	31.9
• Finished goods	10684	63.4	665.4	3349	45.3	38.2
INFORMATION TECHNOLOGY						
IT stock	4966	0.003	0.004	4894	0.003	0.004
IT labor	4966	0.005	0.012	4894	0.005	0.012
Supply chain ERP score: simple	6114	0.287	0.318	4894	0.288	0.313
Supply chain ERP score: employee weighted	6114	0.320	0.349	4894	0.323	0.345
Supply chain ERP score: revenue weighted	6113	0.316	0.353	4894	0.318	0.348
General ERP score: simple	6114	0.335	0.310	4894	0.336	0.303
General ERP score: employee weighted	6114	0.364	0.343	4894	0.365	0.337
General ERP score: revenue weighted	6113	0.360	0.348	4894	0.360	0.342
Supply chain ERP users as % of employees	4168	0.023	0.239	3265	0.026	0.265
General ERP users as % of employees	3567	0.011	0.078	2758	0.011	0.081
InformationWeek rank	48054	0.017	0.128	4894	0.130	0.337
InformationWeek “ranked” indicator	48054	3.1	32.9	4894	25.2	91.7
Principal component of above measures	2452	0.000	2.019	2381	-0.015	2.014
Hitt-Brynjolfsson composite	4966	0.019	0.037	4894	0.019	0.037
FIRM CHARACTERISTICS						
COGS	16100	2621.6	12315.3	4894	4057.7	14978.2
Gross margin (%)	16100	0.316	0.423	4894	0.334	0.169
Capital intensity	15788	0.695	0.196	4873	0.724	0.164
Sales surprise	48054	0.253	0.435	4894	0.608	0.488
Lead time (days)	16054	112.4	1058.4	4894	44.9	46.7
Sigma sales	9868	864.8	3970.8	3461	969.1	4100.4
COGS growth (%)	12193	0.402	13.568	3980	0.095	0.488
T-bill rate	39770	2.042	0.927	4208	2.037	0.927
Total assets	16078	3584.4	16614.6	4894	5160.1	20780.6
PPE, gross	15810	2131.4	10919.1	4873	2766.8	11600.5
Net sales	16101	3665.6	15803.2	4894	5718.6	19329.6
Accounts payable	16073	344.4	1603.4	4894	493.4	1850.0
#employees	6114	4150.8	9268.6	4894	4366.8	9327.5
#executives	7588	9.6	11.1	2738	15.1	15.2
INSTRUMENTAL VARIABLES						
Average year of birth	6976	1951.3	6.6	2488	1950.9	4.8
% with IT majors	7588	0.033	0.089	2738	0.031	0.071
% with science majors	7588	0.304	0.279	2738	0.286	0.224
% with arts majors	7588	0.018	0.065	2738	0.019	0.047

Table 2—Baseline Results (Hypothesis *H1*)

The dependent variable is log days of inventory. The baseline model estimated here is:

$$\iota_{it} = \sum_{y=t-l}^{t} \tau_{iy} + \Delta_{it} + \phi_i + \psi_t + \varepsilon_{it},$$

where ι_{it} is log days of inventory and *i* and *t* index firm and year, respectively. τ is IT, the variable of interest, with up to *l* lags. Δ is a vector of control variables that can affect inventory. φ captures firm effects and ψ, year effects. ε is assumed to be white noise. All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term. Numbers in brackets are standard errors.

		H1: IT effect on inventory			
	Predicted sign	(A) Replication	(B) Replication	(C) Comp + ctrl	(D) +IVs (2SLS)
IT					
Log IT stock				-17.67***	
			-.032*** (.009)	(5.07)	
Log IT labor	-		-.006 (.006)		
General ERP score: simple	-	-.070*** (.026)			
General ERP score: simple, 1 lag	-	-.024 (.021)			
General ERP score: simple, 2 lags	-	-.002 (.021)			
15 complementarities				Yes	
Principal component 1					.413 (2.49)
Principal component 2	-				2.13 (2.17)
INVENTORY CONTROLS					
Gaur, *et al.* (2005)		No	Yes	Yes	Yes
JOINT TEST OF IT VARIABLES					
F		4.30	13.68	3.85	.63
p		.038**	.000***	.000***	.642
N		5306	4590	2118	606
p		.000	.000	.000	.000

*, **, *** means significance at the 10%, 5%, 1% levels. IW=Information Week.

Table 3—Exogeneity of the Instrument Variables

The dependent variables are shown in the column headings. Column (C) replicates (D) of Table 2. All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term. Numbers in brackets are standard errors.

	Increased inventory leads to higher IVs?		A restricted sample: Only inventory decreased
	(A) Exec's average year of birth	(B) % execs with IT majors	(C) Log days of inventory
INVENTORY			
Log days of inventory	-.236	-.004	
	(.297)	(.004)	
Log days of inventory, 1 lag	-.018	-.001	
	(.302)	(.004)	
IT			
Principal component 1			-.554
			(.296)
Principal component 2			-.761
			(.584)
Inverse Mill's ratio			-6.84
			(7.99)
INVENTORY CONTROLS			
Gaur, et al. (2005)	-	-	Yes
JOINT TEST OF INVENTORY, IT			
F	.63	1.58	1.61
p	.426	.209	.174
N	4474	4797	152/48054
p	.001	.000	.000

*, **, *** means significance at the 10%, 5%, 1% levels.

Table 4—Moderators (*H2a* and *H2b*)

The dependent variable is log days of inventory. All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term. Numbers in brackets are standard errors.

	H2a: Supply chain, between firms			*H2b:* Inventory type, within firm		
	(A) Manuf	(B) Wholesale	(C) Retail	(D) Raw mat	(E) WIP	(F) Fn goods
IT						
Principal component 1	-.754***	.217	.945***	-1.754	-2.208	-.543
	(.020)	(.643)	(.333)	(1.581)	(1.441)	(.423)
Principal component 2	-.325***	.000	1.116***	-2.418	-2.813	-.432
	(.043)	(.000)	(.136)	(2.466)	(2.224)	(.388)
CONTROLS						
Netessine and Rudi (2006)	Yes	Yes	Yes	-	-	-
Gaur, *et al.* (2005)	-	-	-	Yes	Yes	Yes
JOINT TEST OF IT VARIABLES						
F	51.0	.13	372.5	.57	.68	.84
p	.000	.877	.000	.685	.610	.503

*, **, *** means significance at the 10%, 5%, 1% levels.

Table 5—Mediators (*H3*)

The dependent variables are shown in the column headings: Growth, Diversification (Divers), and Log days of Inventory (Invt). All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term. Numbers in brackets are standard errors.

	IT effect mediated by asset growth	
	(A) Growth	(B) Inventory
IT		
Principal component 1	.538***	-2.222***
	(.118)	(.212)
Principal component 2	.972***	-3.038***
	(.208)	(.364)
GROWTH		
Asset growth		.308***
		(.057)
CONTROLS		
Gaur, *et al.* (2005)	Yes	Yes
Log assets		.132*
		(.075)
Log property, plant, equipment		-.133***
		(.036)
JOINT TEST OF IT VARIABLES		
F	7.59	78.48
p	.000	.000

*, **, *** means significance at the 10%, 5%, 1% levels.