Inventory and its relationship with profitability: evidence for an international sample of countries

Serguei Roumiantsev
roumiant@wharton.upenn.edu

Serguei Netessine
netessine@wharton.upenn.edu

The Wharton School
University of Pennsylvania

January 2007

Abstract: In this paper we empirically study inventory dynamics for a large sample of publicly held companies from nine countries in the Organization for Economic Co-operation and Development (OECD). Our goals are (i) to identify differences in inventory behavior across countries and across different types of inventories and (ii) to link inventory behavior with financial performance. We find that higher sales, accounts payable, product margins, sales uncertainty and sales growth are all associated with higher total inventories, both in the pooled sample and within most countries. Depending on the country, our model explains between 76% and 95% of the variation in the absolute inventory. Interestingly, we find that economies of scale in inventory management exist only in four countries out of nine in our sample, whereas four other countries exhibit diseconomies of scale an in the remaining country inventory is growing linearly with sales. Furthermore, we use a system of equations and a semi-parametric model to estimate the behavior of three different types of inventories across countries (raw materials, work in process and finished goods) and find similar results for the work in process and finished goods inventories. Surprisingly, the raw materials inventories exhibit a negative association with margins and accounts payable. We further link components of the cash cycle with accounting profitability as measured by return on sales (ROS). We find that, after controlling for other relevant segment- and firm-level effects, shorter total cash cycles, lower inventory levels and shorter accounts payable are all positively associated with ROS. Surprisingly, among the three inventory components, only raw materials inventories have a consistent and negative association with ROS.

Keywords: inventory, empirical research, international operations, operations-finance interface

1. Introduction

This paper contributes to the emerging stream of empirical literature studying inventory behavior for international samples of companies. We propose an econometric model that reliably explains firm-level inventory dynamics across different countries and links inventory management with financial performance. In particular, we study a large sample of publicly held companies from nine of the 30 countries in the Organization for Economic Co-operation and Development, or OECD (Canada, Germany, France, Great Britain, Japan, Korea, the Netherlands, Switzerland and the United States), using annual data from the COMPUSTAT Global database. Companies in our sample come from the retail, wholesale, manufacturing and mining segments, and we use data for the period from 1994 to 2004.

At first glance there appear to be significant differences across countries in terms of amounts of inventories held, time trends, and inventory composition by type (raw materials, work in process and finished goods). However, our econometric model, which utilizes variables that have proven useful in the previous studies that focused on US-based companies, indicates that both absolute and relative inventory levels can be reliably explained by sales, product (gross) margins, sales uncertainty, accounts payable and sales growth. All of these variables are positively and statistically significantly associated with inventories and, depending on the country, the model explains between 76% and 95% of inventory fluctuations. The single most significant difference across countries is inventory elasticity with respect to sales: we observe economies of scale in inventory management in Japan, the United States, the Netherlands and Great Britain, but we also observe diseconomies of scale in Canada, Germany, Switzerland and France, and in Korea inventories grow linearly with sales.

Using a subsample of manufacturing companies only, we study the behavior of the three inventory types by jointly estimating the relationships among inventory components (raw materials, work in process and finished goods) and explanatory variables using a semi-parametric model and applying the logic derived from classical multi-echelon inventory literature. We find that most of our findings for total inventories continue to hold for the finished goods and the work-in-process inventories as well. At the same time, we discover that the raw materials inventories behave very differently: they exhibit a negative association with margins and accounts payable.

Next, we attempt to establish a link between inventory management and accounting profitability as measured by return on sales (ROS). We find that ROS is significantly negatively associated with a firm's cash cycle and its components: positively with accounts payable, negatively with days of inventory, and negatively with days of accounts receivable outstanding. Analysis of the three inventory components indicates that, among all components of the cash cycle, raw material inventories have the highest and most significant negative association with ROS.

Our main contributions are threefold. First, we show that a simple econometric model reliably explains inventory dynamics even across different countries. Second, we propose a novel econometric model to estimate jointly three different types of inventories and show that, with a few notable exceptions, different inventory types behave similarly across countries. Third, we provide evidence for a relationship between a company's inventory levels and its profitability and identify raw materials inventory as the inventory component most strongly linked to profitability.

The rest of the paper is organized as follows. In Section 2 we provide a literature review, and in Section 3 we describe our data sample. In Section 4 we analyze the dynamics of aggregate inventories across countries, and in Section 5 we use multi-echelon inventory model logic to analyze the behavior of the three inventory components. In Section 6 we attempt to link inventory management with accounting performance, and we conclude in Section 7 by discussing limitations and potential directions for future studies.

2. Literature review

Literature related to our study spans theoretical and empirical inventory research in operations management and empirical studies in economics, as well as finance/accounting literature that aims to explain the profitability of firms. Thus, we will provide a concise summary of only the most relevant papers while emphasizing work that specifically deals with international data at the firm level.

Inventory modeling has been an area of intensive inquiry in operations management and operations research. Some classical texts describing the variables that are widely used in classical inventory models are Silver et al. (1998) and Cachon and Terwiesch (2005). At the same time, only a few recent papers in operations management analyze inventories at the firm level empirically and try to reconcile inventory behavior observed in practice with the behavior predicted by the models. Most of these papers look at US firms, and some of them analyze the link between inventory management and financial performance. Gaur et al. (2005) examine firm-level inventory behavior among retailing companies. They propose a model explaining differences in inventory turns across companies and create an adjusted measure of inventory turns that is better suited to gauge the operational metrics of retailers. Gaur et al. (2005) also find that inventory turnover for retailing firms is positively associated with both capital intensity and sales surprise, and is negatively associated with gross margins. Gaur and Kesavan (2006) extend this work by studying effects of firm size and sales growth on inventories. Gaur et al. (1999) demonstrate that the financial excellence of retailing companies comes from various operational strategies that may involve low or high product margins and low or high inventory turns in different retailing segments. Rajagopalan and Malhotra (2001) study trends in inventory levels at US firms over time to test the widely held belief that inventory management has improved due to the introduction of just-in-time (JIT) practices and information technology (IT) system implementations. Using a large sample of firms from the US Census Bureau that includes both private and public companies, they find that material and work in process inventories decreased in most of the two-digit Standard Industrial Classification (SIC) industries from 1961 to 1994. Furthermore, in some segments there were greater improvements in the post-1980 period when JIT practices were adopted. Continuing this line of work, Chen et al. (2005, 2007) find decreasing trends for relative inventories (inventory as days of sales), in both the manufacturing and the wholesaling sectors for the period 1981-2003. They also find somewhat mixed evidence in the retailing sectors, with a downward trend starting only in 1995. Using an event study approach, they show that firms with abnormally high inventories have abnormally poor long-term stock returns. They also find that the relationship between Tobin's q and abnormal inventory (which is a standardized deviation from the sector-wide inventory mean) is weak in cross-section for all sectors. Lai (2005) provides empirical evidence that (i) markets cannot differentiate between "good" and "bad" inventory, (ii) markets punish firms when they can tell that inventory decisions are "bad" (e.g., write-offs) and (iii) inventory levels do not statistically explain firm value. Roumiantsev and Netessine (2005a) propose an econometric model that explains firm-level inventories using mean sales, sales uncertainty, accounts payable, inventory holding costs and product margins. Hendricks and Singhal (2005) show that supply chain disruptions are very costly to public companies, since they cause a substantial loss in market value. Singhal (2005) analyzes the long-run stock price effects of excess inventories. He finds that the stock market partially anticipates excess inventory situations, and the negative effect of excess inventory is significant: mean abnormal returns due to excess inventory are -37.22% in the sample. Roumiantsev and Netessine (2005b) do not find a relationship between the return on assets and inventory levels but instead find that superior earnings are associated with the speed of change/responsiveness in inventory management.

Research on inventories in the international context is scarce. Lieberman and Asaba (1997) and Lieberman and Demeester (1999) compare inventory management and JIT practices in the Japanese automotive industry with those in the US automotive segment. They find that Japanese companies are leaner on average and that the introduction of JIT systems among US companies has helped them to become leaner as well. Lieberman et al. (1999) study the dynamics of inventory levels for automotive suppliers in North America. They combine a survey and secondary plant-level data to show that inventory levels are affected by both technological and managerial factors in a manner consistent with classical inventory theory. Namely, they show that inventory levels at selected plants increase with setup costs, item costs per unit and production lead times, and that inventories are lower for plants in which the workforce engages in making process improvements. Surprisingly, the plants of Japanese companies in North America hold no less inventory than plants of American companies. Lai (2006a, 2006b) studies inventory behavior for publicly held retailing companies across different countries, using a combination of three databases – Edgar, COMPUSTAT and Bureau van Dijk. He finds that public infrastructure impacts inventory management, that country effects do help to explain inventory heterogeneity and that the “global determinism” hypothesis that is popular in the strategic management literature is not supported. Finally Prasad and Babbar (2000) provide a summary of empirical research on international operations management and note that the statistical evidence for foreign countries is not broad and is largely survey-based.

Inventory has also long been a focus of research in the field of macroeconomics, but mostly from the standpoint of aggregate dynamics across the US economy. (In contrast, our study and most previously mentioned studies operate at the firm level.) As summarized in Ramey and West (1999), economists have proposed models based on stock-adjustment and production-smoothing to link inventory with production, sales and GDP so as to show the two main stylized facts about inventory behavior: (i) that aggregate economy-level inventory dynamics have a pro-cyclical nature and (ii) that there is a persistent relationship between sales, production and inventory in the form of production smoothing (i.e., reduced variability of production as compared to variability of sales). To date, researchers have found little evidence consistent with these models and instead have discovered that (i) historically, based on seasonal data, production in the US has been more volatile than sales (thus contradicting the linear-quadratic stock-adjustment model) and (ii) the imputed speed of inventory adjustment based on linear-quadratic model assumptions is unrealistically low. Kahn et al. (2002) report evidence that economy-wide supply-demand matching has significantly improved over time but at the same time Comin and Mulani (2004) find that firm-level sales volatility has increased due to higher product variety, shorter product life cycles and other microeconomic factors.

In the accounting/finance domain, Kothari (2001) provides a detailed summary of research on capital markets and notes that inventory issues have been addressed in just a few papers. The most relevant among these is the work of Thomas and Zhang (2002), which analyzes various ways in which changes in balance sheet items impact stock returns. Interestingly, they find that the negative relationship between accruals and future abnormal returns is mainly due to inventory changes. Thomas and Zhang (2002) propose three explanations for this phenomenon that are related to the mis-pricing of accruals but cannot find statistical support for them in the data. They state that it is not enough to look at balance sheet items and accounting identities alone – operational understanding of such issues in the context of expected versus unexpected demand shifts is required.

To summarize, empirical studies of inventories have been largely limited to the US economy (with the exception of papers by Lai 2006a, 2006b), and even these studies (with the exception of Rajagopalan and Malhotra 2001) do not analyze the three different types of inventories. Moreover, evidence for the relationship between inventory management and financial performance is quite limited and pertains only to the US economy.

3. Sample description

To obtain firm-level financial data for international companies we use the COMPUSTAT Global Industrial/Commercial database (COMPUSTAT Global Vantage), which is available through Wharton Research Data Services and contains annual data on a variety of financial variables. COMPUSTAT Global has been widely used in studies of international finance and accounting because it contains data that has been standardized across countries (see Ball et al. 2000), thus allowing a comparison of international and US companies operating in similar industries. Government agencies often prefer COMPUSTAT Global (over Amadeus or OSIRIS databases) for studying international taxation and international transfer pricing issues.

Work by Rajan and Zingales (1995), Kothari (2001) and Joos and Lang (1994) discusses issues involved in working with an international sample of companies. Among these issues, they note that differences in depreciation, taxation and legal systems are most crucial when analyzing accounting data across countries. However, as noted in Gebhardt (2000), publicly held international companies (especially those incorporated in developed countries) are converging in their accounting reporting standards since their shareholder base has become increasingly global. Thus, comparisons across international companies (including analyses of operational data) are becoming easier to do. Moreover, Joos and Lang (1994) conclude that it is acceptable to compare financial ratios, at least across EU countries.

There are several limitations with respect to using global accounting data to assess the operating performance of companies. Naturally, we expect that country effects matter. Additionally, as Lai (2006a) and Rajan and Zingales (1995) discuss, companies listed in COMPUSTAT Global are subject to a two-level survivorship bias. First, only active, publicly listed companies are reported. Second, the average size of listed companies is likely to vary across countries and, moreover, the database is likely to be biased towards larger companies, especially for countries that might have a different structure of capital markets (e.g., a higher fixed cost of going public or the prevalence of private finance). Moreover, not all international companies report consolidated accounting data and, as Rajan and Zingales (1995) state, companies with unconsolidated balance sheets can have lower leverage ratios and a different valuation of assets. This variation becomes larger when analyzing taxation issues on the boundary of on-balance-sheet and off-balance-sheet activities (financial instruments, etc.). Therefore, an adjustment should be made before comparing numbers across countries. However, these considerations are unlikely to affect our analysis because operating data on sales and costs is probably the least distorted across companies and countries, allowing us to perform our analysis after controlling for relevant effects.

We form our sample as follows. We start with the total population of companies in the COMPUSTAT Global database and select active companies in the manufacturing (SIC 2000-3999), wholesale and retail (SIC 5000-5999) and minerals and mining sectors excluding construction (SIC 1000-1499, 1800-1999). This is done for the total period available to us in the database, 1994 to 2004. We select only those international companies that are assigned to a specific industry sector so as to make samples from different countries comparable. Next, we exclude companies that have been in mergers, acquisitions, buyouts, liquidations, and delisting activities, as well as companies that had at any point a nonzero "comparability status" field (indicating any combination of the above non-operating activities). At this stage we have 89 countries represented in the sample. We omit countries with fewer than 50 companies in the database, leaving us with 20 countries. Out of these countries we decided to concentrate on OECD countries only. The focus on OECD countries, with their better-developed accounting standards, helps to reduce the potential impact of political, inflationary and other non-operating factors. Matching the list of the 30 OECD countries with the remaining 20 countries in our sample leaves us with nine countries: Canada, Switzerland, Korea, Germany, France, Great Britain, the Netherlands, Japan and the US. We further refine the sample to create an almost balanced panel by making sure that positive data on sales, cost of goods sold and inventories is available for at least eight years for every company. We then remove outliers by excluding the top and bottom 1% of companies in terms of both the ratio of inventory to sales and the percentage growth in sales. Finally, we are left with 29,642 firm-year observations, from which we create an additional subsample of manufacturing companies only (SIC 2000-3999) that have at least eight years of positive data on raw materials, work in process and finished goods inventories. This subsample contains 7,966 firm-year observations.

To ensure an adequate comparison across countries, we express all data in 2006 US dollars using 12-month average exchange rates available from the Global Insight database through Wharton Research Data Services. This averaging helps us to remedy the structural effect of the introduction of the Euro in 1997-1998. In line with recommendations from accounting and finance literature (Kothari 2001), we do not use constant US dollars, because country- and segment-specific inflation indexes are too aggregate and cannot control for different price indexes in input (cost) versus output (sales) data. The reason is that managers typically make their decisions based on nominal (current) price-level data. In addition to using information from comparable years, we also utilize variables expressed in the same units (e.g., inventory measured at cost), and we use relative values to eliminate price effects. We do not control for inflation because it has been very minimal over the past decade in the nine OECD countries in our sample.

Table 1 provides a summary of our sample. An average company in our sample has $1.99B in sales and carries 76 days of inventories. As in other papers studying international companies (e.g., Lai 2006a, 2006b), Japan and the US dominate the sample, and smaller countries have, on average, larger companies. Distributions of sales and inventories are consistently right-skewed as was also observed by Lai (2006a), Roumiantsev and Netessine (2005a) and Rajan and Zingales (1995). Companies in Japan and the US are somewhat similar in size, with mean annual sales around $2B and median annual sales around $300M. Companies in Korea and Germany are much larger on average, because these smaller samples are affected by tails. Simple parametric t-tests for mean differences (at the 5% significance level) show that an average company in Korea is both leaner and has a shorter cash cycle than the average company in the pooled sample. Likewise, an average company in France, Switzerland or

Germany holds greater inventory and has a longer cash cycle than the average company in the pooled sample.

In the subsample of companies with the three types of inventories, we observe that, on average, 30% of the total inventory in dollar value is held in raw materials, another 30% is held in work in process and the remaining 40% is held in finished goods inventory. However, it should be noted that this dollar value is probably biased towards finished goods inventory, since this category includes not only direct materials but also direct labor and overhead costs that are capitalized into inventory assets. Interestingly, proportions of raw materials, work in process and finished goods inventories are relatively stable across countries. (This hypothesis cannot be rejected by a t-test.)

As a part of our exploratory analysis, we consider time series dynamics of absolute and relative inventories (expressed in days of sales, measured at cost) (see Graph 1). We perform formal fixed effects analysis to understand the trend dynamics for inventories across countries and find that, for an average US company in the sample, days of inventory has a negative time coefficient of -0.77. The same coefficient for an average Swiss, German and Dutch company is -1.79, -1.39 and -1.20, correspondingly. In contrast, the average Japanese company has a positive time coefficient of 0.44, whereas other countries did not exhibit statistically significant time trends in their inventories. For US companies these results are broadly (in the pooled sample) in line with the results of Chen et al. (2005, 2007) and Rajagopalan and Malhotra (2001). However, time trends explain only a very small portion of both between- and within-firm variation in the annual data across countries, and, moreover, industry- and country-specific results clearly vary. Testing for statistically significant time trends in ratios of raw materials and work in process inventories did not yield significant results, so these ratios appear to be stationary over time.

4. Explaining inventory dynamics across countries

The previous section indicates that country-level cross-sectional and time effects alone do not explain a significant portion of variations in inventories. Thus, to explain inventory dynamics across countries we take an approach that uses firm-level variables that are likely to be related to firms' inventory decisions, as discussed in Lieberman and Asaba (1997), Lieberman et al. (1999), Gaur et al. (1999, 2005), Gaur and Kesavan (2006) and Roumiantsev and Netessine (2005a). Namely, we modify the methodology in Roumiantsev and Netessine (2005a) that links, in a log-log econometric model, inventory behavior with firm-level explanatory variables: sales, margins, sales uncertainty, accounts payable and sales growth. These variables have been shown to explains inventory behavior in the US economy well, and in this section we check whether the applicability of this model extends to the broad international sample we formed. Based on the previous literature, we expect that all these variables have positive associations with inventories. The model we use to analyze absolute and relative inventory behavior is as follows:

$$\begin{aligned}
&\log I_{\mathrm{cit}} = A_0 + b_1 \log S_{cit} + b_2 \log M_{cit} + b_3 \log \sigma_{cit} + b_4 \log DAP_{cit} + b_5 G_{cit} + v_{ci} + ct_c + \varepsilon_{cit} t,\\
&t \text{ – time index,}\\
&i \text{ - firm index,}\\
&c \text{ - country index.}
\end{aligned} \tag{1}$$

In model (1), I_{cit} is the annual inventory (note that we also run this model for the relative inventory measured in average days of inventory, DI_{cit}), S_{cit} is the cost of goods sold (COGS, or annual sales expressed in input prices to make it comparable to inventory values), M_{cit} is the relative gross margin (the difference between annual sales and COGS divided by sales), σ_{cit} is the standard deviation of sales, DAP_{cit} is the average days of accounts payable outstanding and

G_{cit} is the annual percentage sales growth rate. We calculate σ_{cit} by estimating a model that de-trends sales using the ARMA(1,1) technique and takes squares of residuals. We select this model because it yields the smallest mean squared error in our dataset, and it is also more robust to outliers, since it has fewer lags than alternative ARMA models.

We also considered including interest rates into the model (using a three-month T-bill) as a proxy for inventory holding costs, but they were consistently statistically insignificant, which is in line with the results of Blinder and Maccini (1991) and Roumiantsev and Netessine (2005a). Another alternative was to use a weighted average cost of capital (WACC) that is firm-specific (see Roumiantsev and Netessine 2005a), but in order to calculate the WACC for non-US companies we would need detailed stock market information for different financial markets as well as a set of efficiency assumptions that might not hold consistently across countries. Therefore, we excluded interest rates from the final analysis. We checked the correlation structure for independent variables both in pooled data and by country and found that the correlation matrix coefficients are small enough (not exceeding 10% to 20%) so that one can expect to have almost orthogonal regressions, and therefore coefficients would be robust with respect to the set of independent variables. Model (1) is a one-way fixed-effects model. Since the time dimension is short, we model it by explicitly including the time trend (as suggested in Reiss and Wolak 2005). Time-invariant fixed effects v_{ci} allow us to capture potentially unobserved firm heterogeneity.

We report pooled and country-specific estimates in Table 2, both for absolute and relative inventories (to save space, we only report the relative inventory regression in the pooled sample). First, we observe that insights from the previous literature for US companies also hold across countries quite consistently. The association between sales and absolute inventory is positive and statistically significant in the pooled sample (the coefficient is .939) and for all countries. The association between gross margin and absolute inventory is positive and statistically significant in the pooled sample (the coefficient is .166) and for all countries except The Netherlands. The association between sales uncertainty and absolute inventory is positive and statistically significant in the pooled sample (the coefficient is .003) and for France, Japan and the US (for other countries it is insignificant). The association between accounts payable and inventory is positive and statistically significant in the pooled sample (the coefficient is .185) and for all countries except Germany. The association between sales growth and inventory is positive and statistically significant in the pooled sample (the coefficient is .071) and for Canada, Japan and the US (for other countries it is insignificant). Time trend is negative and statistically significant for Switzerland, Germany, France and the US. Surprisingly, Japan exhibits a positive and statistically significant time trend and, moreover, the trend in the pooled sample is also positive and statistically significant.

We observe that absolute inventory levels exhibit economies of scale (concavity, coefficient less than one) in the US, Japan, Great Britain and the Netherlands, but exhibit diseconomies of scale (convexity) in France, Canada, Germany and Switzerland. To ensure the robustness of this finding we analyze Model (1) for both the relative inventory and for one-digit SIC industries within each country, but observe similar results. Therefore, we conclude that different countries might have very different structures of fixed costs, possibly due to differences in flows of goods and geographic conditions. Germany exhibits the greatest diseconomies of scale with elasticity of inventory to sales around 1.5, whereas the US exhibits the greatest economies of scale with elasticity around .8, an estimate that is consistent with results from the quarterly data in Roumiantsev and Netessine (2005a). In the pooled sample, we observe slight economies of scale (the coefficient is -.060).

Among other striking differences we note that Germany has by far the highest elasticity of inventory with respect to changes in gross margins – on average, a German company in the sample increases inventory levels by 1.7% when gross margins increase by 1%, whereas in other countries the increase in inventory levels is .2% on average. (Similar results hold for relative inventories.) Further, in our annual data, demand uncertainty explains fluctuations in inventories to a lesser extent than in the quarterly data of Roumiantsev and Netessine (2005a): a 1% increase in demand uncertainty is associated with only a .003% increase in absolute inventory levels. We believe that this result is logical because the annual data does not capture the seasonal effects that cause large fluctuations in demand, so the usefulness of employing annual data to study second-order effects is limited.

As is evident from the above discussion, sales dynamics are the single largest predictor of inventory behavior both in terms of the magnitude of coefficients and in terms of the variance that it explains (see Graph 2, which shows incremental between- and within-firm variance in inventories explained by the model). We see that, in the pooled data, sales dynamics explain 55% of within-firm variation and 75% of between-firms variation. Additional variables add incremental improvements of around 1-2% per variable. These variance decomposition results are relatively robust across countries, so Model (1) performs consistently well for the chosen sample of OECD countries.

We performed a variety of robustness checks and also tried alternative model specifications. We verified that estimation results are robust with respect to time by splitting the sample into two subsamples – 1994-1998 and 1999-2004. We also analyzed differences in residuals of Model (1) across countries. Using regressions with dummy variables we statistically cannot reject the hypothesis that the residuals for absolute inventories and relative inventories have the same first and second moments, suggesting that Model (1) explains a majority of both within- and between-firm inventory variations across countries.

5. Analysis of three inventory components

A majority of empirical analysis of inventories both in economics and operations management has focused on finished goods inventories alone, even though the most volatile component of inventories has always been raw materials inventory (see Ramey and West 1999 and Humphreys et al. 2001). Motivated by analysis in these two papers as well as theoretical studies in operations management that attempt to bring different inventory types together in multi-echelon models (see Clark and Scarf 1960 and Cohen and Lee 1988), we study in this section the behavior of three different types of inventories across countries.

In analyzing the dynamics of inventory components we propose to employ a paradigm that is traditional in operations research models. The basic idea introduced in Clark and Scarf (1960) is to conceptually separate independent and dependent demands that drive inventories in different echelons of the supply chain and to use dynamic programming to obtain inventory stocking decisions under demand uncertainty. Production scheduling, multi-echelon and multi-period inventory optimization models as well as production systems (MRP/MRP II/ERP) widely use this approach; see the discussion in Silver et al. (1998). Using this paradigm, we propose an econometric model to estimate jointly the behavior of three inventory components: raw materials, work in process and finished goods. An alternative is to use the classical approach from economics (see Ramey and West 1999 and Humphreys et al. 2001), whereby inventory levels are related to demand for inventory components which constitute inputs into the production function along with capital and labor. In this case the firm solves the static cost minimization problem while facing an ex-ante imposed cost function (Ramey and West 1999 use the generalized McFadden cost function, and Humphreys et al. 2001 use a combination of semi-parametric quadratic cost functions for labor, production, input materials and inventory holding costs). This approach is appealing, because it creates separable closed-form first order conditions (Euler equations) that can be solved for the required parameters. Although this approach is acceptable for the economy- and segment-level data, we believe that firm-level analysis should be rooted in multi-echelon inventory theory with general cost functions that might include fixed costs.

We use Model (1) for the total firm-level inventory as the baseline and denote by X the set of explanatory variables that drive the panel of inventory dynamics. That is, we let $X = \{LogS, LogM, LogDAP, Log\sigma, G\}$, where panel indexes are omitted for the sake of simplicity. If we assume that the firm behaves rationally by minimizing costs, the three components of absolute inventory – finished goods (*IF*), work in process (*IW*) and raw materials (*IR*) – will behave according to the multi-echelon logic: in any two adjacent echelons the upper echelon will fulfill dependent demand from the lower echelon, which in turn will depend on the inventory positions in the lower echelons as well as on the independent variables *X*. Moreover, all inventories will be impacted by the entire set *X* of variables. As a result, we propose to model inventory components semi-parametrically as follows:

$$(2) \qquad \begin{cases} (2.1)\ LogIF_{cit} = A^f + b^f X_{cit} + c^f t + v^f{}_{ci} + \varepsilon^f{}_{cit}, \\ (2.2)\ LogIW_{cit} = A^w + \theta^{wf} LogIF_{cit} + b^w X_{cit} + c^w t + v^w{}_{ci} + \varepsilon^w{}_{cit}, \\ (2.3)\ LogIR_{cit} = A^r + \theta^{rw} LogIW_{cit} + \theta^{rf} LogIF_{cit} + b^r X_{cit} + c^r t + v^r{}_{ci} + \varepsilon^r{}_{cit}. \end{cases}$$

In this system of equations we have error terms that might be correlated with each other, and we also include separate unobservable fixed effects for each inventory component. The system of equations for endogenously determined levels of inventories in Model (2) is already in a reduced form because the flow of materials moves in only one direction over time—from the upper echelon to the lower echelon—and finally fulfills demand (assuming that product returns are negligible). Therefore, it is possible to estimate Model (2) directly without coping with solving the structural form equations or estimating them indirectly (Greene 1997).

We estimate Model (2) using the subsample of our data that includes only manufacturing companies that have positive data on all three components of inventory. We first-difference each equation to remove fixed effects and thereafter estimate this differenced system of equations jointly using the SUR method to increase estimation efficiency (Greene 1997). Table 3 reports estimation results of Model (2) in the pooled sample for both absolute and relative inventory levels, the latter denoted by *DIR*, *DIW* and *DIF*, correspondingly.

From Table 3 we observe that three inventory components move together: all corresponding coefficients are positive and statistically significant. We also see that results for the finished goods and the work-in-process inventories are quite consistent with our earlier results for total inventories. Namely, the association between these two inventory types and sales, margin and accounts payable is positive and statistically significant. The relationship between sales uncertainty and work-in-process inventory is positive and statistically significant as well, but it is insignificant for the finished goods inventory. Likewise, the relationship between sales growth and the finished goods inventory is positive and statistically significant, but it is insignificant for the work-in-process inventory.

We observe drastically different behavior of the raw materials inventory which is negatively and significantly associated with both gross margins and accounts payable. This unexpected result might be due to the fact that the raw materials inventory is the echelon in the supply chain farthest from the set of factors X. Thus, for example, when margins increase, the raw materials inventory might be depleted, whereas finished goods and work in process inventories increase. As expected, the raw materials inventory exhibits positive and statistically significant association with sales and sales growth, but the relationship with sales uncertainty is insignificant.

We note that upper echelons of the supply chain exhibit progressively higher economies of scale in inventory management (the raw materials inventory is more concave in sales than the work in process inventory, which is more concave than the finished goods inventory). This finding is probably due to the fact that the fixed costs incurred in production are larger than the fixed costs incurred in distribution and sales. Another interesting result is that the raw materials inventory exhibits much higher elasticity to sales growth than the other components of inventory (the coefficient of .607 vs. -.020 and .094). This finding is in line with predictions from popular investment guides that high raw materials inventory indicates pre-positioning of raw materials in the anticipation of sales growth (see, for example, page 122 in O'Glove 1987). Finally, Graph 3 shows the incremental percentage of overall variance explained by each variable in Model (2). Similar to Model (1), sales explains a large proportion of variance in inventory.

We conducted several robustness checks. We used relative instead of absolute inventory as a dependent variable (see Table 3) and found that signs and significance of coefficients remained qualitatively the same with two exceptions. First, coefficients with respect to sales were now negative indicating economies of scale. Second, the relationship between sales growth and both the finished goods and the work-in-process inventories were negative and statistically significant while the relationship between sales growth and the raw materials inventory remained positive and statistically significant. This observation further supports the idea that the company might be pre-positioning the raw materials inventory in anticipation of sales growth while depleting the finished goods and the work-in-process inventories. We further verified that our results hold quite consistently across countries, and we do not report these results here to save space. By analyzing residuals of Model (2), we verified that the heterogeneity of inventory components is removed by using the specified set of explanatory variables: we cannot reject the hypothesis that residuals across countries are homogeneous in terms of their first and second conditional moments.

6. Inventory behavior and accounting performance

As discussed in Kothari (2001), there is still little evidence as to whether quantifiable operational metrics are associated with better financial performance. Recent attempts to link inventory management and financial performance empirically provide mixed evidence. Chen et al. (2005, 2007) document that firms with abnormally high inventories have abnormally poor long-term stock returns (but not vice versa). Singhal (2005) finds significant negative abnormal stock returns after announcements of excess inventory. Lai (2005) finds that low-inventory firms obtain better valuations as measured by Tobin's q. However, Roumiantsev and Netessine (2005b) do not find an association between inventories and return on assets. In this section we wish to understand whether there is a link between inventory and profitability in the international sample of companies and whether such results differ by inventory types.

In our analysis of the international sample we choose return on sales (ROS) as a measure of accounting performance. The main reason for this choice is that different taxation and asset amortization laws across countries make it hard to make meaningful comparisons using either return on equity (ROE) or return on assets (ROA); see Ball et al. (2000). Nevertheless, we checked our results using ROA as another measure of performance and most of them continued to hold. The underlying logic for the analysis was introduced in McGahan and Porter (1997, 2002). We explain *ROS* in the panel using segment-level effects (segment-average ROS denoted by *SROS*, segment growth denoted by *SG*), firm controls (firm size measured by log of COGS or *LogS*, sales growth denoted by *G,* and a dummy variable *V* for "volatility" which is 1 if standard deviation of sales is above the median for a specific firm in a specific country for a specific year) and the relative "leanness" of the firm in terms of the cash cycle (*CC*) and its components (days of accounts payable *DAP*, days of inventory *DI* and its subcomponents *DIR*, *DIW* and *DIF*, and average days of accounts receivable outstanding denoted by *DAR*). In line with previous literature (McGahan and Porter 1997), we expect *SROS*, *SG* and *LogS* to be positively associated with *ROS* (larger companies existing in more profitable and faster growing segments have higher profitability). In line with literature in accounting, we expect that DAR is negatively associated with ROS while DAP is positively associated with ROS. In line with previous empirical literature in operations management, we expect that inventory and its components will be negatively related to ROS. We estimate three different models:

$$\begin{cases} (3.1)\ \ ROS_{its} = A^0 + (\vec{k},\vec{Y}) + b^1 LogCC_{its} + ct + \nu_i + \varepsilon_{its}, \\ (3.2)\ \ ROS_{its} = A^0 + (\vec{k},\vec{Y}) + b^1 LogDAP_{its} + b^2 LogDI_{its} + b^3 LogDAR_{its} + ct + \nu_i + \varepsilon_{its}, \\ (3.3)\ \ ROS_{its} = A^0 + (\vec{k},\vec{Y}) + b^1 LogDAP_{its} + b^2 LogDIR_{its} + b^3 LogDIW_{its} + b^4 LogDIF_{its} + b^5 LogDAR_{its} \\ \qquad\qquad + ct + \nu_i + \varepsilon_{its}. \end{cases}$$

where *Y={SROS, SG, LogS, G, V)* introduced for the ease of presentation. Essentially, we try to explain profitability by components of cash cycle with industry controls and firm effect.

We report the results of estimating this model using fixed-effects estimation in Table 4. It should be noted that these regressions for countries with smaller samples (e.g., Korea, for which results are insignificant overall, and the Netherlands) can be more efficiently estimated using OLS regressions, but we use fixed-effects estimations for all countries to make the results comparable. For Model (3.1) we confirm (in the pooled sample and for most countries) the usual directions for segment- and firm-level effects: larger companies and companies in more profitable segments are, on average, more profitable while companies facing more volatile demand have consistently lower ROS. Furthermore, we see that longer cash cycles *CC* are associated with lower ROS. For example, for an average US company, a decrease in cash cycle from the sample average of 97 days to 87 days is associated with a 5% increase in ROS. For country-specific regressions, only Great Britain exhibits the opposite behavior – higher ROS is associated with longer cash cycles.

Furthermore, we apply Model (3.2) to identify specific components of the cash cycle that are associated with better financial performance. Overall, we find that being lean in inventory management and fast in collecting payments is almost equally positively associated with ROS, while it is on average better to have longer accounts payable. These relationships are statistically significant in the pooled sample but vary somewhat by country. Canada and Great Britain, for example, exhibit positive relationships between inventories and ROS while Germany, the US and The Netherlands exhibit negative relationships. Continuing with Model (3.3), we look for inventory types that exhibit an association with ROS. As before, we use a subsample of manufacturing firms to answer this question and we find that, after controlling for other factors, only days of raw materials are consistently negatively associated with a higher ROS. This relationship is remarkably strong, as it holds in the pooled sample and for all individual countries (although it is not statistically significant for Switzerland and Great Britain). The relationship both between days of work in process inventory and ROS and between days of finished goods inventory and ROS is statistically insignificant in the overall pooled sample; however, in several cases the relationships are statistically significant. Specifically, the relationship between days of work in process inventory and ROS is negative and statistically significant in Germany, France and the Netherlands. The relationship between days of finished goods inventory and ROS is negative and statistically significant in France, Japan and the Netherlands. But otherwise these relationships in the pooled sample and in other countries are insignificant.

We verified the robustness of our findings by using one-year-forwarded ROS and found that most of our results continue to hold except for the negative association between ROS and sales growth – sales growth in the current period is, on average, consistently positively associated with future ROS (i.e., growth in the current period appears to be reflected in next year's ROS).

7. Summary

In this paper we aimed to explain firm-level inventory behavior as well as link it to financial performance using an international sample of companies. We addressed this key question by analyzing annual inventories of public companies from nine OECD countries, specifically Canada, France, Germany, Great Britain, Japan, Korea, Switzerland, the Netherlands, and the US. We found that the behavior of inventories differs significantly across countries. Companies in Japan and Korea are much leaner on average, whereas companies in France and Switzerland tend to hold a lot more inventory, with time trends varying across countries as well. Despite this heterogeneity, our econometric model that relies on variables that proved useful in explaining inventory behavior for the US companies seems to explain a majority of the variation in inventories across countries and companies. In particular, we find that both relative and absolute inventories increase with sales, sales uncertainty, accounts payable, product margins and sales growth. However, we also note that the economies of scale in inventory management that have been shown to persist in the US (Roumiantsev and Netessine 2005a, Gaur and Kesavan 2006) do not seem to work a several other countries which exhibit diseconomies of scale. This is a truly interesting finding and we hope that future research will be able to shed some light on these striking differences.

Moreover, we propose a new econometric model to analyze jointly the behavior of three inventory components – raw materials, work in process and finished goods inventories. To accomplish this task we used logic from multi-echelon inventory models to separate independent and dependent demands and estimated the three inventory types jointly as a system of equations. We observed that, both in the pooled sample and across countries, the finished goods inventory and the work-in-process inventory relate to explanatory variables (sales, margins, uncertainty, accounts payable and sales growth) in the same predicted way as the total inventory. Surprisingly, the raw materials inventory consistently behaves differently with respect to margins and accounts payable. To our knowledge, this is the first attempt at modeling joint behavior of different inventory types and more research is needed to explain different behavior of raw materials inventory.

Next, we attempted to link inventory dynamics with accounting performance as measured by ROS. After controlling for relevant segment- and firm-level effects, we found that longer cash cycles are negatively associated with ROS, a result which is quite robust in the pooled sample and across countries (with Great Britain being the only exception). Next, we decomposed the cash cycle into its components and found that, on average, days of accounts payable are positively associated with ROS, whereas inventory and days of accounts receivable are negatively associated with ROS. Overall, our results with respect to inventory are consistent with findings of Chen et al. (2005, 2007) and provide further evidence that the relationship between inventory and profitability is not straightforward. It is, however, different from findings in Roumiantsev and Netessine (2005b) where no link between inventory levels and financial performance was found. We believe that this difference might due to utilization of the annual data in the current study (vs. quarterly data in Roumiantsev and Netessine 2005b).

After further splitting inventory into its three components (using a subsample of manufacturing companies) we found that raw materials inventory has the strongest negative association with ROS. Since previous research did not differentiate inventory types when linking inventory and profitability, understanding better why only raw materials inventory plays a role in explaining ROS could be another potential research direction.

Among the obvious limitations of our analysis is the distortion that might be introduced by accounting standards that differ across countries. Moreover, different countries are unevenly represented in the COMPUSTAT Global database, and firm sizes vary greatly across countries, which might cause a double survivorship bias. Finally, there are standard concerns regarding limitations of the accounting data which might be too aggregate to analyze detailed inventory dynamics. Despite these potential drawbacks, our analysis sheds light on important issues concerning inventory dynamics. With this work we hope to promote the analysis of operational and inventory issues from a more international perspective as well as to link the field of empirical research in operations management more firmly with other areas such as finance and accounting.

References

Ball R., S.P. Kothari and A. Robin. 2000. The Effect of International Institutional Factors on Properties of Accounting Earnings. *Journal of Accounting and Economics*, Vol. 29, 1-51.

Blinder A. and L. Maccini. 1991. Taking Stock: A Critical Assessment of Recent Research on Inventories, *Journal of Economic Perspectives*, Vol. 5, 73-96.

Cachon G. and C. Terwiesch. 2005. *Matching Supply with Demand: An Introduction to Operations Management.* Second edition, The McGraw-Hill Companies.

Chen H., Frank M., and O. Wu. 2005. What Actually Happened to the Inventories of American Companies between 1981 and 2000? *Management Science*, Vol. 51, 1015-1031.

Chen H., Frank M., and O. Wu. 2007. US Retail and Wholesale Inventory Performance from 1981 to 2003. Forthcoming, *Manufacturing and Service Operations Management*.

Clark A. and H. Scarf. 1960. Optimal Policies for a Multi-Echelon Inventory Problem. *Management Science*, Vol. 4, 475-491.

Cohen M.A. and H.L. Lee. 1988. Strategic Analysis of Integrated Production-Distribution Systems: Models and Methods. *Operations Research,* Vol. 36, 216-228.

Comin D. and S. Mulani. 2004. Diversing Trends in Macro and Micro Volatility: Facts. Working paper, New York University.

Gaur V., M. Fisher and A. Raman. 2005. An Econometric Analysis of Inventory Turnover Performance in Retail Services. *Management Science*, Vol. 51, 181-194.

Gaur V., M. Fisher and A. Raman. 1999. What Explains Superior Retail Performance? Working paper, New York University.

Gaur, V., S. Kesavan. 2006. The Effects of Firm Size and Sales Growth Rate on Inventory Turnover Performance in the U.S. Retail Sector. Forthcoming in N. Agrawal and S. Smith (editors). *Retail Supply Chain Management*, Kluwer Publishers.

Gebhardt G. 2000. The Evolution of Global Standards in Accounting. Brookings-Wharton Series on Financial Services, 341-368.

Greene W. 1997. *Econometric Analysis*. Third edition. Prentice-Hall, NJ.

Hendricks K. and V. Singhal. 2005. Association Between Supply Chain Glitches and Operating

Performance. Management Science, Vol. 51, No. 5, 695-711.

Humphreys B., L. Maccini and S. Schuh. 2001. Input and Output Inventories. *Journal of Monetary Economics*, Vol. 47, 347-375.

Joos P., and M. Lang. 1994. The Effects of Accounting Diversity: Evidence from the European Union. *Journal of Accounting Research*, Vol.32, 141-168.

Kahn J., M. McConnell and G. Perez-Quiros. 2002. On the Causes of the Increased Stability of the US Economy. *Economic Policy Review.*

Kothari S.P. 2001. Capital Markets Research in Accounting. *Journal of Accounting and Economics*, Vol. 31, 105-231.

Lai R. 2005. Inventory and the Stock Market. Working paper, Harvard University.

Lai R. 2006a. The Geography of Retail Inventory. Working paper, Harvard University.

Lai, R. 2006b. Does public infrastructure reduce private inventory? Working paper, Harvard University.

Lieberman M.B. and S. Asaba. 1997. Inventory Reduction and Productivity Growth: A Comparison of the Japanese and U.S. Automotive Sectors. *Managerial and Decision Economics*, *Special Issue on Japanese Technology Management*, Vol. 18, 73-85.

Lieberman M.B. and L. Demeester. 1999. Inventory Reduction and Productivity Growth: Linkages in the Japanese Automotive Industry. *Management Science*, Vol. 45, 466-476.

Lieberman M.B., S. Helper and L. Demeester. 1999. The Empirical Determinants of Inventory Levels in High-Volume Manufacturing. *Production and Operations Management*, Vol. 8, 44-55.

McGahan A. and M. Porter. 1997. How Much Does Industry Matter, Really? *Strategic Management Journal*, Vol. 18, 15-30.

McGahan A. and M. Porter. 2002. What Do We Know About Variance in Accounting Profitability? *Management Science*, Vol. 48, 834-851.

O'Glove, T.L. 1987. *Quality of Earnings*. Free Press, New York, NY.

Prasad S. and S. Babbar. 2000. International Operations Management Research: Classification, Analysis, and Agenda. *Journal of Operations Management*, Vol. 18, 209-247.

Rajagopalan S. and A. Malhotra. 2001. Have US Manufacturing Inventories Really Decreased? An Empirical Study. *Manufacturing and Service Operations Management*, Vol. 3, 14-24.

Rajan R. and L. Zingales. 1995. What Do We Know about Capital Structure: Some Evidence from International Data. *Journal of Finance*, Vol. 50, 1421-1461.

Ramey V. and K. West. 1999. Inventories. Chapter 13 in the *Handbook of Macroeconomics*, Vol. 1, Elsevier Science.

Reiss P. and F. Wolak. 2005. Structural Econometric Modeling: Rationales and Examples from Industrial Organization. Forthcoming in *Handbook of Econometrics,* Vol. 6.

Roumiantsev S. and S. Netessine. 2005a. What Can Be Learned from Classical Inventory Models: a Cross-Industry Empirical Investigation. Working paper, University of Pennsylvania.

Roumiantsev S. and S. Netessine. 2005b. Should Inventory Policy Be Lean or Responsive? Evidence for US Public Companies. Working paper, University of Pennsylvania.

Silver E., D. Pyke and R. Paterson. 1998. *Inventory Management and Production Planning and Scheduling*. Third edition, John Wiley and Sons.

Singhal V. 2005. Excess Inventory and Long-Term Stock Performance. Working paper, Georgia Institute of Technology.

Thomas J. and H. Zhang. 2002. Inventory Changes and Future Returns. *Review of Accounting Studies*, Vol. 7, 162-187.

Table 1: Data summary

	Sample with data on total inventories							Subsample with data on 3 types of inventories				
Country	Firm-year Observations	Sales, $M		Total Inventory, Days		Cash Cycle, Days		Firm-year Observations	Raw Materials Inventory, Days		Work in Process Inventory, Days	
		Mean	Median	Mean	Median	Mean	Median		Mean	Median	Mean	Median
Canada	298	594	214	81	74	74	64	182	37	23	23	15
France	196	10361	1710	127	103	126	128	153	37	29	36	13
Germany	188	16514	1467	107	92	151	124	180	24	23	27	11
Great Britain	1,411	1170	175	90	78	89	81	1,000	30	25	17	12
Japan	21,251	1581	295	69	56	78	68	2,642	17	12	24	13
Korea	142	10068	4517	45	42	53	50	124	20	16	10	7
Switzerland	173	4135	377	112	93	135	127	133	26	24	30	28
The Netherlands	179	14820	1822	85	83	100	92	116	32	18	28	14
US	5,804	2360	418	94	82	97	86	3,436	36	28	29	18
Total	29,642	1992	311	76	63	84	75	7,966	23	16	24	13

Graph 1: Dynamics of (from the bottom) days of raw materials inventory, raw materials plus WIP inventory and total inventory.

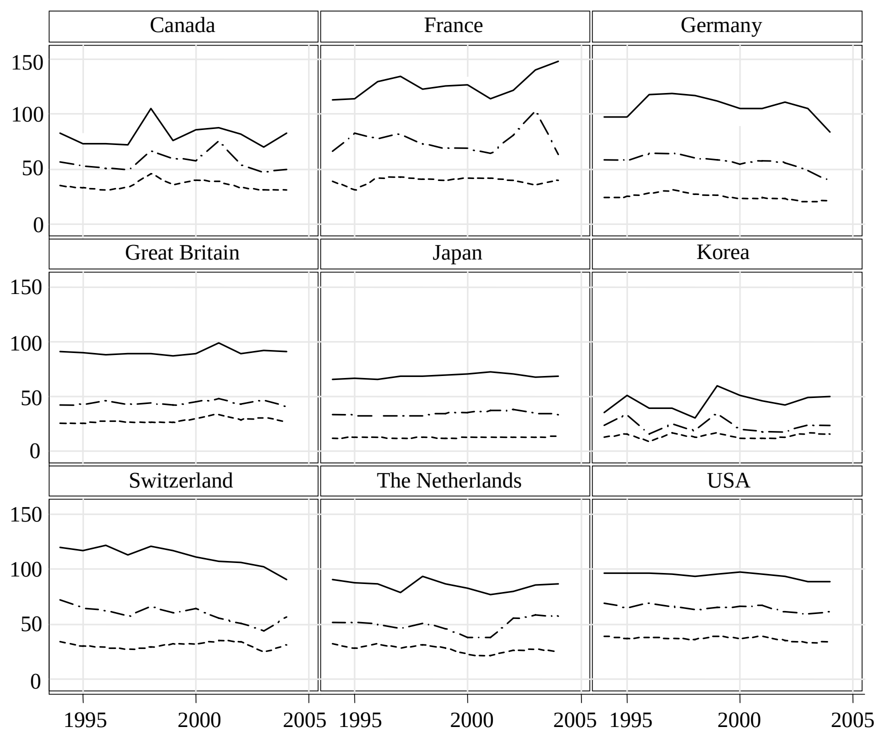

Table 2: Absolute and relative inventory estimates for Model (1)

	Absolute inventory										Relative Inventory
LogI	Canada	Switzerland	Germany	France	Great Britain	Japan	Korea	The Netherlands	US	Total	LogDI
LogS	1.180*** (0.088)	1.080*** (0.060)	1.503*** (0.055)	1.189*** (.058)	0.896*** (.023)	0.970*** (0.007)	1.00*** (0.118)	0.801*** (0.072)	0.813*** (0.011)	0.939*** (0.005)	-0.060*** (0.006)
LogM	0.249*** (0.060)	0.289*** (0.137)	1.794*** (.185)	0.623*** (0.167)	0.164*** (0.041)	0.174*** (0.011)	0.542*** (0.125)	0.043 (0.138)	0.097*** (0.015)	0.166*** (0.008)	0.166*** (0.008)
Logσ	-0.01 (0.029)	0.013 (0.018)	-0.001 (0.020)	0.024* (.012)	-0.002 (0.011)	0.003** (0.001)	-0.003 (0.033)	-0.023 (0.018)	0.008** (0.004)	0.003** (0.001)	0.004** (0.002)
LogDAP	0.355*** (0.070)	0.093* (0.059)	-0.039 (0.033)	0.132** (0.069)	0.287*** (0.026)	0.209*** (0.008)	0.207*** (0.089)	0.266*** (0.089)	0.146*** (0.012)	0.185*** (0.006)	0.185*** (0.006)
G	0.124* (0.076)	-0.001 (0.081)	-0.035 (0.109)	0.024 (0.075)	0.021 (0.015)	0.099*** (0.007)	0.035 (0.067)	-0.034 (0.097)	0.087*** (0.014)	0.071*** (0.005)	0.071*** (0.005)
t	-0.002 (0.012)	-0.026*** (0.006)	-0.022*** (0.008)	-0.029*** (0.005)	-0.002 (0.003)	0.004*** (0.001)	0.010 (0.013)	0.007 (0.007)	-0.006*** (0.001)	0.001** (0.001)	0.001** (0.001)
Constant	-3.592*** (0.548)	-1.749*** (0.431)	-2.97*** (0.381)	-2.59*** (0.534)	-2.01*** (0.169)	-2.489*** (0.057)	-2.311*** (0.991)	-1.09** (0.596)	-1.54*** (0.081)	-2.096*** (0.042)	3.803*** (0.042)
Within R^2	57%	78%	86%	80%	61%	52%	70%	65%	66%	57%	7%
Between R^2	90%	93%	96%	95%	91%	78%	93%	90%	84%	81%	18%
Overall R^2	88%	92%	95%	94%	89%	76%	90%	90%	85%	79%	17%
F-statistic	50	80	147	101	281	3204	42	42	1509	5305	299

Note: here and elsewhere, *, **, and *** denote statistical significance at the 10%, 5% and 1% levels.

Graph 2: Variance explained by Model (1)

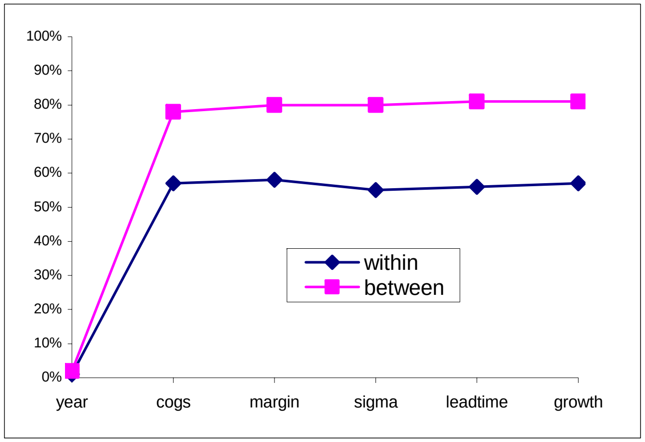

Table 3: Behavior of three inventory components, Model (2) fixed effects estimation

Absolute inventory components pooled analysis				Relative inventory components pooled analysis			
	LogIR	LogIW	LogIF		LogDIR	LogDIW	logDIF
LogIW	0.102*** (0.010)			LogDIW	0.121*** (0.010)		
LogIF	0.053*** (0.012)	0.087*** (0.015)		LogDIF	0.088*** (0.011)	0.138*** (0.015)	
LogS	0.758*** (0.023)	0.772*** (0.027)	0.973*** (0.014)	LogS	-0.102*** (.017)	-0.158*** (0.024)	-0.026*** (0.006)
LogM	-0.104*** (0.022)	0.094*** (0.028)	0.161*** (0.021)	LogM	-0.063*** (0.021)	0.114*** (0.028)	0.161*** (0.021)
Logσ	0.005 (0.006)	0.022*** (0.008)	0.006 (0.005)	Logσ	0.005 (0.006)	0.021*** (0.008)	0.006 (0.005)
LogDAP	-0.098*** (0.019)	0.239*** (0.025)	0.138*** (0.016)	LogDAP	-0.045*** (0.019)	0.275*** (0.025)	0.138*** (0.016)
G	0.607*** (0.02)	-0.020 (0.026)	0.094*** (0.015)	G	0.462*** (0.019)	-0.154*** (0.026)	-0.094*** (0.015)
t	-0.004 (0.001)	-0.033*** (0.003)	0.002 (0.002)	t	-0.004** (0.002)	-0.035*** (0.003)	0.002 (0.002)
Constant	-1.913*** (0.013)	-3.366*** (0.170)	-2.813*** (0.105)	Constant	2.844*** (0.129)	1.884*** (0.173)	3.086*** (0.105)
Overall R^2	70%	58%	72%		10%	7%	7%

Graph 3: Variance explained by Model (2)

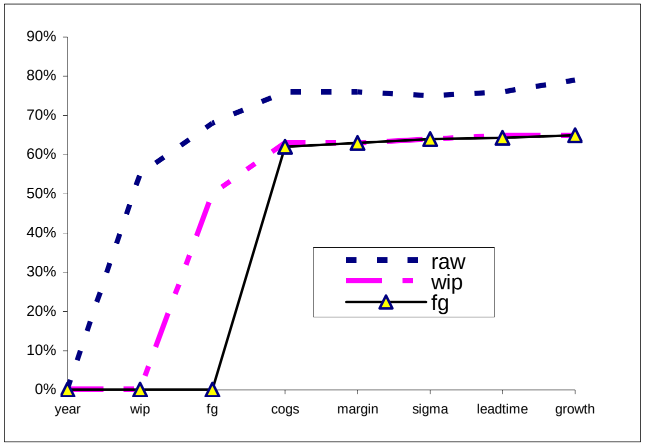

Table 4: Explaining ROS behavior – segment-level, firm-level and cash cycle effects – Model (3.1)

	Canada	Switzerland	Germany	France	Great Britain	Japan	Korea	The Netherlands	USA	Total
	0.837***	0.748***	0.844***	0.830***	0.717***	0.731***		0.825***	0.766***	0.861***
SROS	(0.059)	(0.060)	(0.09)	(0.072)	(0.051)	(0.031)		(0.068)	(0.054)	(0.015)
	0.000	0.037***	-0.007*	-0.004	0.000	0.031***		-0.001	0.001	0.001**
SG	(0.001)	(0.012)	(0.005)	(0.004)	(0.0007)	(0.002)		(0.001)	(0.003)	(0.000)
	-0.155***	0.011	-0.005	-0.010***	0.048***	0.015***		-0.020***	0.055***	0.020***
LogS	(0.056)	(0.008)	(0.009)	(0.003)	(0.010)	(0.001)		(0.009)	(0.007)	(0.002)
	-0.025	0.001	-0.008***	-0.004***	-0.017***	-0.001*		-0.003	-0.007*	-0.001***
V	(0.032)	(0.003)	(0.003)	(0.001)	(0.007)	(0.0004)		(0.002)	(0.004)	(0.0008)
	0.025	-0.047***	-0.0003	0.004	0.033***	-0.041***		0.004	-0.107***	-0.038***
G	(0.056)	(0.013)	(0.014)	(0.007)	(0.010)	(0.002)		(0.012)	(0.008)	(0.002)
	-0.01***	0.006	-0.004	0.002	0.036***	-0.011***		-0.012**	-0.031***	-0.012***
LogCC	(0.002)	(0.011)	(0.006)	(0.002)	(0.008)	(0.000)		(0.007)	(0.006)	(0.001)
	0.012	0.000	-0.000	0.001	0.000	0.000***		-0.000	-0.004***	-0.001***
t	(0.006)	(0.0008)	(0.001)	(0.001)	(0.001)	(0.000)		(0.001)	(0.001)	(0.000)
	0.764***	-0.099	0.085	0.083**	-0.425***	-0.028***		0.222***	-0.149***	-0.056***
Constant	(0.0293)	(0.079)	(0.075)	(0.039)	(0.075)	(0.009)		(0.084)	(0.049)	(0.013)
Within R^2	65%	70%	57%	58%	18%	14%		65%	13%	17%
Between R^2	6%	70%	59%	63%	17%	1%		2%	7%	11%
Overall R^2	28%	69%	57%	62%	16%	3%		22%	7%	13%
F	53	45	27	27	34	364	0.97	31	95	667
Model (3.2): cash cycle decomposed into three components										
	-0.085**	0.003**	0.002	0.010	-0.070***	0.020***		0.012	0.003	0.004**
LogDAP	(0.041)	(0.001)	(0.004)	(0.007)	(0.013)	(0.001)		(0.013)	(0.007)	(0.017)
	0.074***	-0.005	-0.008**	0.004	0.021*	-0.021**		-.029***	-0.006	-0.014***
LogDI	(0.026)	(0.013)	(0.004)	(0.008)	(0.011)	(0.001)		(0.011)	(0.08)	(0.002)
	0.044	-0.001	-0.0001	0.013	-0.014***	-0.008***		0.006	-0.048***	-0.017***
LogDAR	(0.034)	(0.02)	(0.004)	(0.008)	(0.006)	(0.001)		(0.011)	(0.007)	(0.002)
Model (3.3): days of inventory decomposed into 3 components										
	-0.216***	-0.006	-0.030***	-0.025***	-0.003	-0.004***		-0.023**	-0.019***	-0.016***
LogDIR	(0.056)	(0.011)	(0.007)	(.008)	(0.011)	(0.001)		(0.012)	(0.006)	(0.004)
	0.181***	0.005	-0.009**	-0.018***	0.015**	-0.001		-0.017**	-0.002	-0.001
LogDIW	(0.032)	(0.006)	(0.004)	(0.006)	(0.006)	(0.002)		(0.008)	(0.005)	(0.002)
	0.015	-0.009	0.002	-0.042***	0.008	-0.005***		-0.046***	0.001***	-0.003
LogDIF	(0.032)	(0.012)	(0.004)	(0.100)	(0.010)	(0.002)		(0.011)	(0.003)	(0.003)