Inventories and sales uncertainty

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Abstract

We investigate the empirical linkages between sales uncertainty and firms' inventory investment behavior while controlling for firms' financial strength. Using large panels of manufacturing firms from several European countries we find that higher sales uncertainty leads to larger stocks of inventories. We also identify an indirect effect of sales uncertainty on inventory accumulation through the financial strength of firms. Our results provide evidence that financial strength mitigates the adverse effects of uncertainty.

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1 Introduction

It has long been recognized that we can better understand the behavior of the firm as well as the cyclical fluctuations in output by studying the changes in inventory investment.[1] Over the business cycle, inventories constitute the most volatile component of GDP as they are the first in line to absorb shocks. This is due to inventories having low adjustment costs (for instance compared to that of fixed capital investment). Following Metzler (1941), researchers proposed several inventory investment behavior models based on microeconomic principles including production smoothing, stock-out avoidance, accelerator motive, (S,s) inventory models among others, to explain inventory holding behavior of firms.[2] Generally speaking, in these models the marginal cost and benefits of holding inventories determine the inventory investment behavior of firms. Based on the presence of asymmetric information, several researchers including Carpenter et al. (1994), Kashyap et al. (1994), Guariglia (1999), Benito (2005), Guariglia and Mateut (2006) show that inventories are determined by the availability of internal funds.

However, we know very little about how inventories are affected while a firm experiences periods of heightened uncertainty. A careful review of the literature yields only two empirical studies where the linkages between uncertainty and inventory investment are discussed: one study uses aggregate macro level data and the other study uses firm level data. Lee and Koray (1994) investigate the association between sales uncertainty and inventory behavior for the US wholesale and retail trade sector and show that the variance in sales does not affect inventory behavior in either sector. Bo (2001), in contrast, focuses on firm level data and uses a small panel of Dutch companies (770 observations) to investigate the impact of demand uncertainty. She finds that demand uncertainty (measured by the volatility of sales) has a positive and significant impact on inventory investment. Surprisingly, there are no other studies in the literature that investigate the effects of volatility on

[1] See including Blinder and Maccini (1991), Metzler (1941), Abromowitz (1950).

[2] See for instance Blinder and Maccini (1991) and West (1995) for a summary of theoretical and empirical studies on inventory investment accumulation.

firms' inventory investment. To have a better grasp on the behavior of inventory accumulation we examine to what extent uncertainty affects firm's inventory investment directly and if uncertainty distorts inventory accumulation indirectly through its effects on other firm specific variables, in particular variables that capture financial market frictions.[3]

In contrast to the empirical research on the inventory accumulation problem, the literature on the fixed investment behavior of the firm has extensively considered the direct and indirect effects of uncertainty. In particular, researchers have demonstrated that uncertainty may exert an indirect effect on fixed capital investment through firm leverage, cash holdings or cash flows.[4] This is not too surprising as it has been established that both uncertainty and financial market imperfections affect fixed investment behavior of firms. Hence, during periods of heightened uncertainty, as potential lenders cannot evaluate firms' credit worthiness, a manager may be forced to reduce borrowing or pay a premium to raise external funds impacting the firm's fixed investment behavior. Similarly, uncertainty can affect a firm's retained earnings altering the manager's course of action due to the presence of financial constraints. When we turn to understand the inventory accumulation behavior of a firm, along with other factors, we expect to find that a firm's inventories would also respond to uncertainty directly. Furthermore, as uncertainty affects firm specific variables through its impact on the financial strength of the firm, we expect to find that inventories should be indirectly affected as well.

In this paper, we specifically examine the direct and indirect effects of firm specific uncertainty on firm's inventory accumulation behavior. Our investigation concentrates on the impact of sales uncertainty and implements a dynamic inventory model to scrutinize direct and indirect effects of sales uncertainty on inventory accumulation while we control for firms' financial strength. The empirical model is implemented using panels of manufacturing firms from several continental European countries—including Belgium, Finland,

[3]Neither Lee and Koray (1994), nor Bo (2001) consider the role of financial market frictions in their investigations.

[4]See for instance Baum et al. (2010a, 2010b), Bloom et al. (2007).

France, Italy, Portugal, and Spain—to provide a comprehensive evidence.[5] In our investigation, we use the same model across all countries rather than competing models so that we can stress those commonalities across countries. Our data covers the period 1999-2007 and are obtained from Amadeus.

Our findings can be summarized as follows. We find that sales uncertainty has a positive impact on inventories indicating that firms facing high demand uncertainty build up inventories to avoid stock-out. However, we also find that the inventory build-up declines as firms hold more liquid assets or extend more trade credit relative to what they receive from their suppliers. This implies that firms that are financially unconstrained do not increase their stocks to demand shocks and tend to respond more effectively. This observation, which is significant for almost all countries in our data set can be attributed to the ability of a less constrained firm to adapt to changes in demand more easily than a constrained firm which cannot alter its production pattern due to constraints. The reason is that a less constrained firm has the means to purchase an extra unit of capital, hire labor quickly or outsource production over the business cycle.

The rest of the paper is constructed as follows. Section 2 presents the modeling framework and discusses the methodology we employ in our investigation. It also lays out the approach we implement to generate firm specific uncertainty. Section 3 documents the data. In section 4, we present our empirical findings. Section 5 concludes the paper.

2 The model

We implement a variant of the stock adjustment model proposed by Lovell (1961), which performs well at explaining movements in aggregate inventory data. Using a similar approach, recent research in the literature has examined the interlinkages between inventory investment and firms' financial health (see Benito, 2005, Guariglia and Mateut, 2006). This model relates the target stock of inventories to the level of sales and allows for slow adjust-

[5] Potential accounting differences across countries, although the data are obtained from the same source, limit cross country comparisons.

ment of inventories to the desired level. In our case, while controlling for firms' financial strength, we augment the model with sales uncertainty to test for the impact of demand uncertainty on firms' inventory accumulation decision. Denoting I as the logarithm of inventories and S as the logarithm of sales, we model the growth in inventories as follows

$$\begin{aligned} \Delta I_{it} &= \alpha + \beta_0 \Delta I_{it-1} + \beta_1 \Delta S_{it} + \beta_2 \Delta S_{it-1} + \beta_3 (I_{it-1} - S_{it-1}) + \beta_4 Fin_{it} + \gamma_1 \sigma_{it} + \\ & \quad + \upsilon_i + \upsilon_t + \upsilon_{jt} + \epsilon_{it} \end{aligned} \tag{1}$$

where subscript i indexes firms, j industries and t time, t = 2001-2007. The first difference of sales and inventories are included in the model to capture the short-run dynamics. The parenthesized term, $(I_{it-1} - S_{it-1})$, is the error correction term which reflects the movement in inventories towards its long-run target. This term portrays the idea that inventories are not adjusted instantaneously due to the presence of adjustment costs. As usual, the idiosyncratic error is depicted by ϵ_{it} and the remaining terms (υ_z) capture the firm, time and industry specific effects.

To measure the financial strength of the firms we add variables that correspond to firms' access to both internal and external resources. Thus, the vector Fin_{it} in equation (1) stands for three variables: $Liquid_{it}$, NTC_{it} and $Debt_{it}$.[6] While liquidity and leverage effects on inventory investment have been long established in the literature (Kashyap et al., 1994, Guariglia, 1999, Benito, 2005), we also incorporate the impact of net trade credit (NTC) following the recent research which consider the link between inventories and funding received from business partners in the form of trade credit.[7] We measure firms' internal sources of finance ($Liquid_{it}$) as the ratio of liquid assets (cash, bank deposits and equivalent) to total assets. $Debt_{it}$ represents loans with short term maturity and NTC_{it}

[6] See Brown et al. (2009) and Brown and Petersen (2009) for a similar approach.

[7] Benito (2005) uses the liquidity ratio and the borrowing ratio defined as debt interest payments to cash flow to measure the financial strength of firms. Guariglia and Mateut (2006) show that the availability of finance from business partners in the form of trade credit positively influences the accumulation of inventories by UK manufacturing firms. Bougheas et al. (2009) find a trade-off between trade credit extended and stocks of inventories as firms attempt to minimize costs when facing demand uncertainty.

denotes net trade credit (i.e. trade credit extended minus trade credit received). Firms' inventory investment is expected to be correlated with access to short term external finance either from banks ($Debt_{it}$) or from their business partners (NTC_{it}). All financial variables are scaled by total assets.

Equation (1) is an error correction model. Due to the adjustment process of inventories, we expect the error correction term, β_3, as well as that of the lagged dependent variable, β_0, to have a negative sign. The coefficients associated with sales and lagged sales are expected to have a positive sign as a firm would increase (decrease) its inventories when it experiences increased (decreased) sales. All financial variables are evaluated at time t. This can be motivated by the fact that inventory investment has low adjustment costs, and can therefore quickly react to changes in financial variables (Carpenter et al., 1994). Therefore, we would expect to find a negative coefficient associated with liquid assets ($Liquid$): as firms increase their liquidity we expect that firms reduce their stocks of inventories. We would also expect to find a negative correlation between net trade credit (NTC) and inventory investment. The reasoning can be explained as follows. On the one hand, there is a positive correlation between purchases on credit from suppliers and stocks of inventories. On the other hand, firms reduce their stocks of goods by selling on credit to their customers. In net terms, the higher the trade credit extended relative to the credit received from suppliers, the lower the inventory investment. Thus, net trade credit, defined as sales on credit minus purchases on credit from suppliers should be negatively related with inventory investment. Finally, better access to external funding ($Debt$) should have a positive effect on inventory accumulation. Hence, we expect to find a positive coefficient associated with $Debt$.

In our next model, we investigate if uncertainty would impact inventories indirectly in addition to its direct impact. In particular, we ask whether sales uncertainty affects inventories through its effects on firms' financial strength. To test this proposition, we augment the above model with an interaction term between uncertainty and financial variables. The model takes the following form:

$$
\begin{aligned}
\Delta I_{it} &= \alpha + \beta_0 \Delta I_{it-1} + \beta_1 \Delta S_{it} + \beta_2 \Delta S_{it-1} + \beta_3 (I_{it-1} - S_{it-1}) + \\
&\quad + \beta_4 Fin_{it} + \gamma_1 \sigma_{it} + \gamma_2 \sigma_{it} * Fin_{it} \qquad (2) \\
&\quad \upsilon_i + \upsilon_t + \upsilon_{jt} + \epsilon_{it}
\end{aligned}
$$

In this model if sales uncertainty affect inventories indirectly, then, γ_2, the coefficient associated with the interaction term between Fin_{it} and uncertainty should be significantly different from zero. In this case, to compute the total impact of uncertainty one should consider both own and indirect effects of uncertainty; i.e. we should compute $\gamma_1 + \gamma_2 \bar{Fin}$ where $\bar{Fin}$ denotes the average value of Fin where Fin is $Debt_{it}$, NTC_{it} or $Liquid_{it}$.

2.1 Generating Sales Uncertainty

Researchers use different approaches to generate measures of firm-specific uncertainty. For instance, Pindyck and Solimano (1993) and Caballero and Pindyck (1996) use a geometric Brownian model to derive the variance of the marginal revenue product of capital. Ghosal and Loungani (2000) proxy the firm-level risk using the standard deviation of the firm's unpredictable profits. Bo and Lensin (2005) use stock price volatility as well as the volatility of the number of employees to measure firm-level uncertainty. More recently, Bloom et al. (2007) measure uncertainty as the standard deviation of firms' daily stock returns.

Given that our dataset contains information on public and non-public firms alike and that non-public firms are much smaller than public firms, we construct a proxy of firm specific uncertainty as in Bo (2001) using sales. We estimate an AR(1) model for sales augmented with time dummies and industry specific time dummies.[8] We then compute the 3-year moving standard deviation of the unpredictable part of sales to construct our uncertainty measure, σ_{it}. Specifically for 2007, we compute the standard deviation of the

[8]Firms are allocated to one of the following nine industrial sectors: metals and metal goods; other minerals, and mineral products; chemicals and man made fibres; mechanical engineering; electrical and instrument engineering; motor vehicles and parts, other transport equipment; food, drink, and tobacco; textiles, clothing, leather, and footwear; and others (see Blundell et al., 1992). Including industry-level time dummies in our regressions ensures that the results are not simply due to cross-industry variations.

residuals obtained from the state space model of sales over 2007, 2006 and 2005. For 2006, the residuals in 2006, 2005 and 2004 are used. The process is repeated similarly for the remaining years. The downside of this approach is the loss of two observations per firm.

We consider the robustness of our findings by using an alternative proxy where we measure sales uncertainty by the standard deviation of the unpredictable part of sales using all current and past residuals. Specifically for 2007, we compute the standard deviation of the residuals obtained from the state space model of sales over 2007 to 2000. For 2006, the residuals in 2006 to 2000 are used. The process is repeated similarly for the remaining years. We also experiment with a 4-year moving standard deviation.

3 Data

To study the impacts of demand uncertainty and firms' financial strength on inventory accumulation, we construct panels of manufacturing firms for several continental European countries using the Amadeus database. Our dataset covers the 1999–2007 period and provides balance sheet information of quoted and unquoted manufacturing firms for European countries including Belgium, Finland, France, Italy, Portugal, and Spain. To avoid the adverse impact of outliers in our investigation, we apply a number of sample selection criteria. We use those firms which have not undergone substantial changes in their composition during the sample period and drop firms whose real assets more than doubled relative to the previous year. We trim one per cent from either end of all variables that we use in our empirical model and remove firms with less than 3 consecutive observations from the dataset. The final data set contains as many as 30,643 firm years for Italy and as little as 2,740 firm years for Finland that have complete data for all variables used in the analysis.

Descriptive statistics for the variables used in the analysis are presented in Table 1. We observe from the table that the average change in inventories and sales is positive in all countries over the sample period. The ratio of net trade credit to total assets (NTC) is always positive meaning that, on average, the manufacturing firms in all our sample countries extend more trade credit than they receive from their business partners. While trade credit received relative to assets is highest in France and Italy, in net terms, firms in Portugal and Spain extend significantly more trade credit than they take relative to firms in Belgium, Finland, France and Italy. This indicates that, despite the fact that trade credit may be an expensive form of external credit, firms in Portugal and Spain use it extensively in comparison to firms in the other countries. This signals that credit in Portugal and Spain may be more restricted than in the other countries. Finish firms use the least amount of trade credit amongst all countries. We also find that bank debt is more extensively used in Italy, Portugal and Spain as the ratios of debt to total assets in these countries are quite high in comparison to the remaining three countries in the dataset. Interestingly, liquidity is lowest in Portugal and Spain. Average uncertainty is highest in Finland but its magnitude appears to be similar to the rest of the countries in the dataset.

The summary statistics highlight systematic differences in the relative use of different sources of finance for firms, even though all countries in our dataset have a bank-based financial system and follow a common monetary policy.[9] We examine in more detail the relationship between inventory investment, sales uncertainty and firms' financial situation in the next section.

4 Empirical findings

We estimate equations (1) and (2) for each country separately using the dynamic panel data (DPD) approach developed by Arellano and Bond (1991), as implemented in Stata by Roodman (2009). All models are estimated in first difference terms to eliminate unobserved heterogeneity using the one-step GMM estimator on unbalanced panels of manufacturing firms extracted from continental European countries. For each model, the J statistic (and the corresponding p-value) is the Hansen–Sargan test statistic and it indicates that the test for over-identifying restrictions is satisfactory. Furthermore, we reject the presence

[9] All six countries in our sample are members of the European Monetary System. Unfortunately, United Kingdom and Germany could not be included in the sample due to missing observations for firms' turnover.

of second-order autocorrelation (AR(2)) validating the use of suitably lagged endogenous variables as instruments.[10] Hence, we do not make any further comments on these tests separately as we discuss our results.

4.1 The basic specification: Direct impact of Uncertainty

We begin our investigation, as defined in Equation (1), by implementing a dynamic model for each country to explore the effects of current and lagged change in sales, the error correction term, variables which control for financial constraints including liquidity, bank debt and net trade credit and sales uncertainty on firms' inventory investment behavior.

Table 2 presents the results for the basic dynamic model given in Equation (1). We observe that the lagged dependent variable is, in general, insignificant except for Portugal. This finding suggests that except for Portugal, firms' inventory investment in the current period is not correlated with their inventory investment in the previous year.[11] Similar to the literature, we find that the effect of the contemporaneous change in sales has a positive effect on inventory accumulation as firms do not want to be caught out of stocks when there is high demand for their goods. Lagged sales, though, does not significantly affect firm behavior as this information is already taken aboard by the long run relation between inventories and sales through the error correction term which takes a negative sign as the theory implies: if the stock of inventories moves further from (closer to) its desired level, future inventory investment accumulation should be higher (lower).

We find that firms' inventory investment is negatively correlated with the volume of net trade credit. The coefficient associated with net trade credit (NTC) is negative for all countries except in the case of Portugal where it happens to be positive but insignificant. The mechanism can be described as follows. Firms increase their stocks of inventories and

[10] All variables lagged twice and further, time and industry specific dummies are employed as GMM instruments.

[11] Guariglia and Mateut (2006) and Benito (2005) include lagged inventory investment as robustness checks only. Guariglia and Mateut (2010) find a negative and precisely determined coefficient in their study which uses a large sample of UK manufacturing firms. The imprecise estimates of the coefficient for lagged inventory investment may be due to the use of annual data.

their account payables when they buy on credit from their suppliers. At the same time, firms reduce their inventories when they sell on credit. Therefore, firms will reduce their inventory stocks as they increase the amount of sales on credit relative to their purchases on credit, i.e. when their net trade credit rises. This finding supports the inventory management model in Bougheas et al. (2009) who find a trade-off between stocks and trade credit extended. Firms avoid holding costly stocks of inventories by selling more on credit and accumulating account receivables when future demand is uncertain. The effect is significant, however, only for Finland, France and Italy. The ratio of debt to total assets is positive for Belgium and France but insignificant for the other countries. We find that cash holdings exert a negative impact for Finland and Portugal, but insignificant for Belgium, France, Italy and Spain.

When we turn to understand the impact of sales uncertainty on inventories, we find that it is positive and significant for all countries, except for Finland, at the 5% significance level or better. A back of the envelope calculation of a one standard change in sales uncertainty leads to approximately a four percent change in inventory accumulation; ranging from as high as 6% in Belgium and Portugal to as low as 1% change in Finland. Overall this observation implies that firms change their stocks significantly as they experience high demand uncertainty to avoid running out of stocks.

4.2 The augmented model: Indirect impact of uncertainty

Having established that sales uncertainty has a direct positive impact on inventory accumulation, we next focus on the implications of Equation (2) where uncertainty also exerts an indirect impact on inventories through the financial stance of the firm. In this model, to understand the full impact of uncertainty, we should consider the direct and indirect effects of uncertainty on inventories, which are captured by γ_1 and γ_2 coefficients as we bear in mind the size of the net trade credit, liquidity or bank debt ratios to total assets. Table (3) provides estimates for the model in Equation (2). Note that the sign and significance of all firm specific variables are similar to those in the previous table. Hence, we rather concentrate on the effects of uncertainty.

When we inspect the direct impact of sales uncertainty, similar to the previous model, we find that it (γ_1) has positive and significant effects in all countries (for Finland at the 10% significance level). This implies that the direct response of firms to an increase in sales uncertainty is to increase their inventories. However, when we scrutinize the indirect effect of uncertainty, we observe that the coefficient that captures the indirect effects of uncertainty assumes negative sign opposing the positive direct uncertainty effects. In particular, the net trade credit-uncertainty interaction term is negative and significant for Belgium, Finland, Italy and Spain at the 10% level or better and insignificant for the other two countries. The liquidity-uncertainty interaction term takes a significant and negative coefficient for Belgium and France at the 10% level or better. The debt-uncertainty interaction is also negative but not significant for any country. This observation suggests that firms can more easily alter their sales strategy or their liquidity ratio than their bank loans in the event of a sales shock. Following increased sales volatility, for instance, firms could sell more on credit (increase their account receivables), increasing thus their net trade credit and reducing their stocks of inventories. Alternatively, due to higher sales uncertainty firms hold lower inventories and higher liquidity. In contrast, firms would find it more difficult to alter their amount of borrowings following a sales shock as raising a loan from banks when the firm faces a negative shock would be hard due to concerns on asymmetric information problems.

4.3 The full impact of uncertainty

In Table 3 we present evidence that uncertainty affects inventory accumulation directly on its own and indirectly through net trade credit and liquidity. Hence, to determine the overall impact of uncertainty on inventory accumulation, one has to take into account both effects simultaneously. Given the extent of complication due to the presence of several terms which are in interaction with uncertainty, we carry out this exercise for only those cases where the associated interaction term $\sigma_{it} * Fin_{it}$ (given the findings presented in

Table (3) Fin is either $Liquid$ or NTC) takes a significant coefficient. The full impact of uncertainty is computed using the following derivative

$$\frac{\partial \Delta I}{\partial \sigma} = \hat{\gamma_1} + \hat{\gamma_2} \times Fin^* \tag{3}$$

In the above expression, the first term captures the direct effect of uncertainty and the second term captures that of the indirect effects. To compute the total effect of uncertainty, we evaluate the above derivative at the 10th, 25th, 50th, 75th, 80th and 90th percentiles of the significant financial variable while the remaining interaction terms are set to their mean values. Therefore, we compute the derivative for Belgium, Finland, Italy and Spain where uncertainty affects inventory accumulation through net trade credit and for Belgium and France where uncertainty affects inventories indirectly through liquidity. These derivatives along with the 95% confidence interval are plotted in Figure 1. Figures 1a-1d plot the results when uncertainty affects inventories through net trade credit, Figures 1e-1f plot the results for when uncertainty affects inventories through liquidity.[12]

Observing Figures 1a-1f we see that the total impact of uncertainty on inventory accumulation is a function of the financial strength of the firm. In all cases, the impact of uncertainty on inventories is positive and significant when the underlying financial strength variable is low, i.e. when the firm is constrained. However, as the financial strength of the firm improves, the positive impact of uncertainty on firms' inventories declines and as a certain threshold of the underlying financial variable is exceeded the impact becomes insignificant. This observation holds true for both net trade credit and liquidity. Furthermore these results are similar in spirit to Baum et al. (2010a, 2010b) who show that the impact of uncertainty on fixed capital investment is related to cash flow or leverage of the company.

[12] Exact figures are available from the authors. Note that net trade credit can be positive or negative depending on whether the firm on the final count is a net lender or net borrower of trade credit.

4.4 Alternative specifications

In Tables 4 and 5, we repeat our investigation using a different proxy for sales uncertainty to check for the robustness of our findings. In particular we generate firm specific uncertainty computing the standard deviation of the unpredictable component of sales from the AR(1) model using all current and past residuals rather than focusing on a measure that uses three of the unexpected components. Specifically for 2007, we compute the standard deviation of the residuals obtained from the state space model of sales over 2007 to 2000. For 2006, the residuals in 2006 to 2000 are used. The process is repeated similarly for the remaining years.[13] Changing the way we define our uncertainty variable does not alter our results. Similar to our earlier findings reported in Table 2, we observe in Table 4 that higher sales uncertainty has a direct and positive impact on inventory investment while inventory accumulation and net trade credit are negatively correlated. Table 5 incorporates both direct and indirect effects of uncertainty into the model. Results in this table are almost a mirror reflection of those presented in Table 3. While higher sales uncertainty directly leads to higher inventory investment, it also has an indirect effect through its impact on the financial stance of the firms. Increased uncertainty lead firms to alter their sales strategy and, therefore, their volume of sales on credit and their desired liquidity. This, indirectly leads to a reduction in firms inventory investment.

In all models we present, the debt uncertainty interaction has no effect on the change in inventories. Hence we re-estimated all our models removing this particular interaction term. The results from this set are similar to those we presented in the text and are not reported for brevity. We also regressed all models using time dummies, instead of industry-time dummies interacted with each other. This change has not lead to any qualitative differences. Both sets of results are available from the authors upon request.

[13] We experiment also with the 4-year moving standard deviation of the unpredictable part of an AR(1) model for sales. This method results in the loss of three observations per firm. These results are not reported and are qualitatively similar to those presented in Tables 2 and 3.

5 Conclusions

In this paper, we empirically investigate the impact of sales uncertainty on firm's inventory investment behavior. In doing so, we investigate the direct as well as indirect effects of uncertainty through movements in financial strength of the firm. To carry out our investigation, we construct panels of manufacturing firms from several European countries including Belgium, Finland, France, Italy, Portugal, and Spain—to provide comprehensive evidence. The investigation uses the same model across all countries rather than competing models so that we can stress those commonalities across countries. Our data covers the period 1999-2007 and are obtained from Amadeus.

Our findings can be summarized as follows. We find that uncertainty has a positive impact on inventory accumulation. This makes sense: as firms are subjected to high demand uncertainty they build up inventories to avoid stock-out. However, we also find that the inventory build-up declines as firms hold more liquid assets or extend more net trade credit indicating that financially less constrained firms can respond to demand shocks efficiently. In other words, financially stronger firms can adapt to changes in demand more easily than constrained firms by altering their production pattern (by hiring more labor or investing in capital stock when needed) or by outsourcing production to potential suppliers over the business cycle as they have the financial means to make such changes. We find that this observation is similar for almost all countries in our data set. Our results also seem to be robust with respect to our measure of sales uncertainty.

DATA APPENDIX

The firm level data are taken from the unconsolidated accounts of manufacturing firms in the Amadeus database. We exclude observations where firms' real assets more than double relative to the previous year and dropped the 1% tails for all variables.

Inventory (I): includes finished goods and work-in-process inventories (current assets stocks) deflated using the aggregate GDP deflator.

Sales (S): includes total turnover deflated using the aggregate GDP deflator.

Net trade credit (NTC): current assets debtors (trade credit extended) minus current liabilities creditors (trade credit received) scaled by total assets.

Trade credit received (TC): current liabilities creditors scaled by total assets.

Loans (Debt): current liabilities loans scaled by total assets.

Liquid assets (Liquid): includes cash and other liquid assets scaled by total assets. Liquid assets are defined as current assets excluding stocks of inventories and trade debtors.

Cash flow (CF): represents cash flow (profit for the period plus depreciation) scaled by tangible assets.

Uncertainty (σ): This is a firm specific measure of sales uncertainty. For each country, we estimate an AR(1) model of the logarithm of sales augmented with time and industry-time specific dummies. Given the panel structure of our data, we employ the first difference GMM estimator. We check for the absence of second-order serial correlation in the residuals (m2) and test for over-identifying restrictions using the Hansen test statistic. Then, we compute the 3-year moving standard deviation of the residual. Specifically for the year 2007, we compute the standard deviation of the residuals obtained from the state space model of sales over 2007, 2006 and 2005. Similarly for year 2006, the residuals in 2006, 2005 and 2004 are used. We winsorize those observations exceeding the 99th percentile. The results are also robust to trimming the data at the 99th percentile. For a similar approach, see Bloom et al. (2007).

We check the sensitivity of our results to generating the variable in two different ways. First, we compute the 4-year moving standard deviation of the residual. Specifically for the year 2007, we compute the standard deviation of the residuals obtained from the state space model of sales over 2007, 2006, 2005 and 2004. Second, we calculate the standard deviation of the unpredictable part of sales using all current and past residuals. Specifically for 2007, we compute the standard deviation of the residuals obtained from the state space model of sales over 2007 to 2000. In 2006, we use residuals over 2006 to 2000, etc.

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Figure 1
Impact of uncertainty at different percentiles of net trade credit

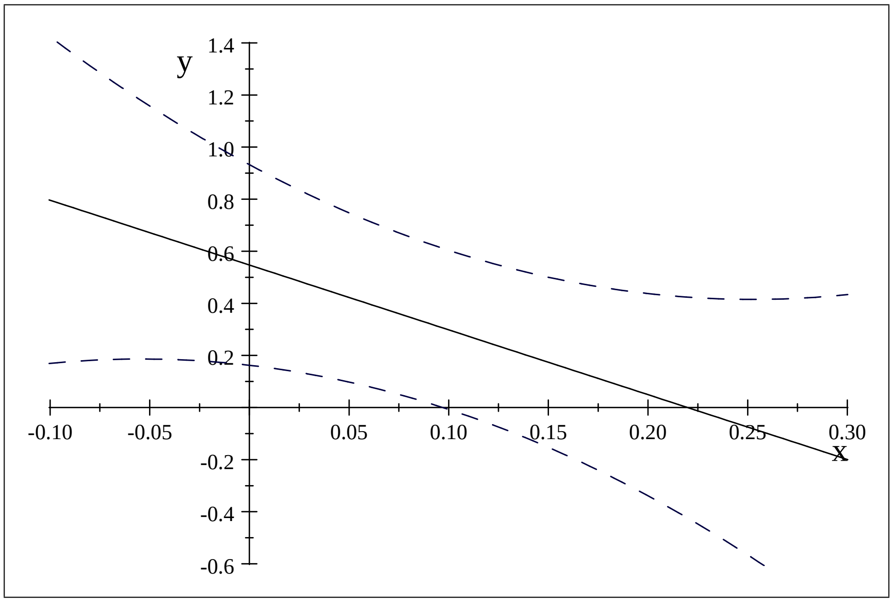

Figure 1a. Belgium

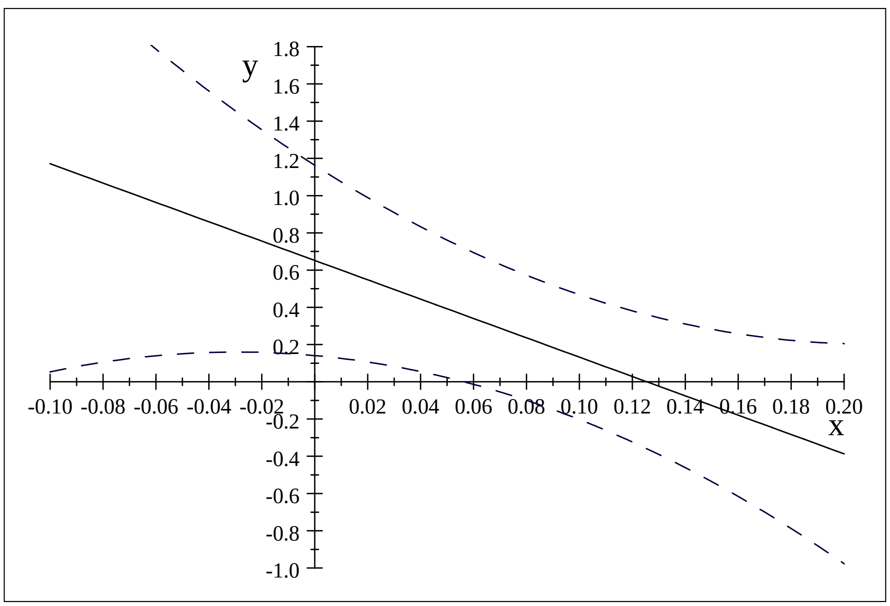

Figure 1b. Finland

Figure 1
Impact of uncertainty at different percentiles of net trade credit

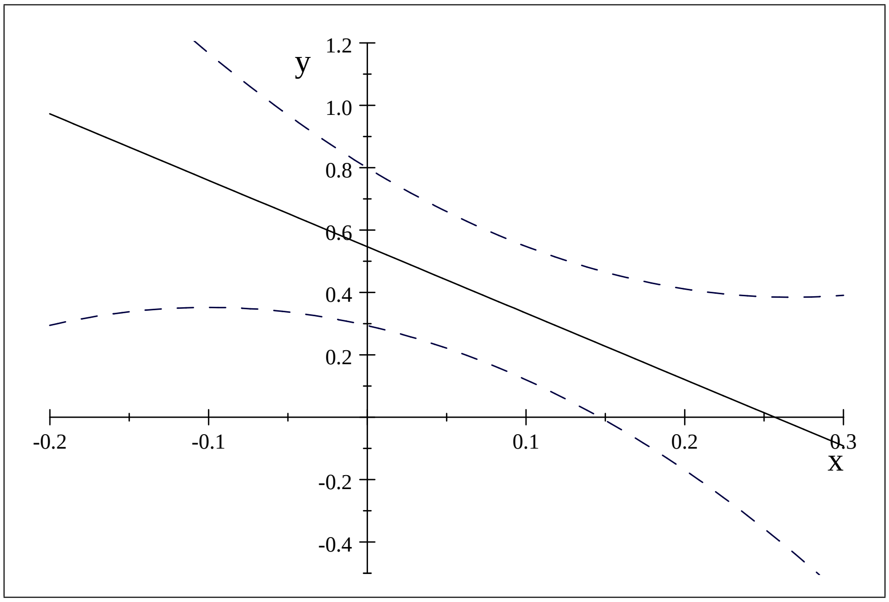

Figure 1c. Italy

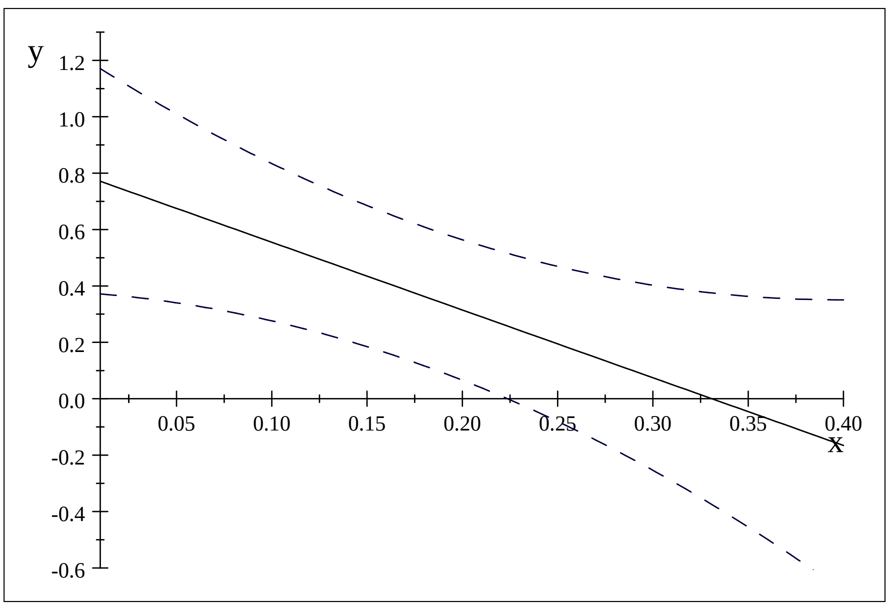

Figure 1d. Spain

Figure 1
Impact of uncertainty at different percentiles of liquid assets

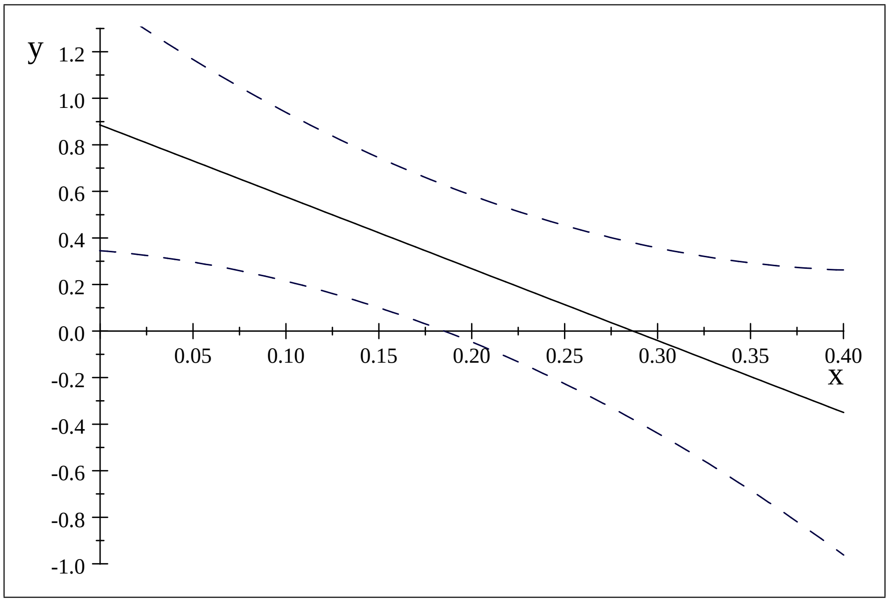

Figure 1e. Belgium

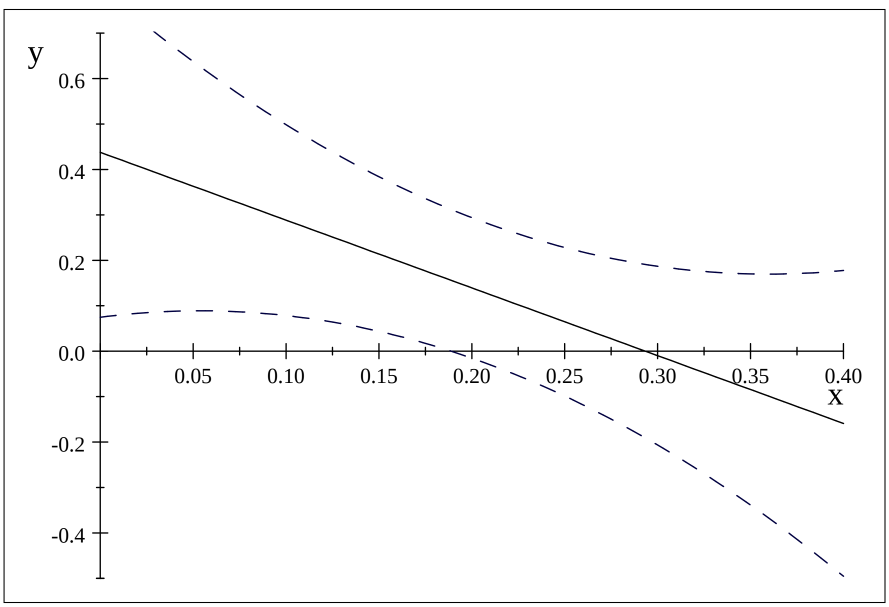

Figure 1f. France

Table 1. Summary statistics

variable	BE	FI	FR	IT	PT	ES
ΔI_{it}	0.025	0.061	0.026	0.057	0.044	0.047
	(0.264)	(0.276)	(0.236)	(0.264)	(0.279)	(0.298)
ΔS_{it}	0.025	0.060	0.028	0.046	0.026	0.036
	(0.150)	(0.180)	(0.144)	(0.153)	(0.151)	(0.155)
NTC_{it}	0.075	0.065	0.059	0.088	0.170	0.169
	(0.137)	(0.103)	(0.149)	(0.152)	(0.152)	(0.155)
TC_{it}	0.235	0.106	0.274	0.272	0.194	0.205
	(0.135)	(0.073)	(0.130)	(0.127)	(0.123)	(0.119)
$Debt_{it}$	0.088	0.036	0.067	0.167	0.115	0.122
	(0.125)	(0.062)	(0.096)	(0.146)	(0.115)	(0.124)
$Liquid_{it}$	0.170	0.215	0.185	0.161	0.066	0.087
	(0.152)	(0.167)	(0.139)	(0.128)	(0.082)	(0.107)
I/S_{it-1}	-2.314	-2.247	-2.233	-1.928	-2.008	-2.213
	(0.788)	(0.649)	(0.793)	(0.720)	(0.808)	(0.826)
σ_{it}	0.108	0.130	0.094	0.097	0.099	0.101
	(0.095)	(0.121)	(0.090)	(0.084)	(0.076)	(0.099)
$Assets_{it}$	55.948	41.114	73.964	37.167	23.512	45.973
	(264.192)	(128.290)	(445.668)	(154.198)	(40.303)	(153.296)
Observations	8593	2740	23345	30643	4488	16019

Notes: The table reports sample means. Standard deviations are presented in parentheses. The subscript *i* indexes firms, and the subscript *t*, time, where t = 2001-2007. *I*: logarithm of inventories; *S*: logarithm of sales; *NTC*: net trade credit is current assets debtors (trade credit extended) minus current liabilities creditors (trade credit received) scaled by total assets; *TC*: current liabilities creditors (trade credit received) scaled by total assets; *Debt*: current liabilities loans scaled by total assets; *Liquid*: current assets excluding stocks of inventories and debtors; σ: firm specific measure of sales uncertainty. *Assets*: total real assets in million euro.

Table 2. Direct impact of uncertainty

	(1) BE	(2) FI	(3) FR	(4) IT	(5) PT	(6) ES
$\Delta\ I_{it-1}$	-0.017	-0.000	-0.023	-0.006	-0.113**	0.001
	(0.037)	(0.049)	(0.022)	(0.027)	(0.053)	(0.028)
$\Delta\ S_{it}$	0.961***	0.811***	0.666***	0.339	0.539**	0.559***
	(0.221)	(0.157)	(0.124)	(0.231)	(0.237)	(0.186)
$\Delta\ S_{it-1}$	0.011	-0.073	-0.037*	-0.014	-0.049	-0.033
	(0.034)	(0.048)	(0.020)	(0.017)	(0.057)	(0.030)
$I/S_{\ it-1}$	-0.805***	-0.823***	-0.659***	-0.629***	-0.581***	-0.724***
	(0.132)	(0.113)	(0.076)	(0.084)	(0.201)	(0.099)
$NTC_{\ it}$	-0.124	-0.779**	-0.404**	-0.353*	0.034	-0.052
	(0.248)	(0.341)	(0.168)	(0.193)	(0.315)	(0.228)
$Debt_{\ it}$	0.491**	0.842	0.583***	0.322	0.268	-0.077
	(0.236)	(0.922)	(0.152)	(0.212)	(0.310)	(0.343)
$Liquid_{\ it}$	-0.031	-0.838***	-0.011	-0.021	-1.386*	-0.326
	(0.179)	(0.245)	(0.130)	(0.158)	(0.756)	(0.264)
$\sigma_{\ it}$	0.608***	0.051	0.181**	0.365***	0.738**	0.485***
	(0.154)	(0.146)	(0.079)	(0.109)	(0.286)	(0.131)
Observations	7194	2280	19344	25466	3699	13263
No of firms	1399	460	4001	5177	789	2756
m1 (p)	0.00	0.00	0.00	0.00	0.00	0.00
m2 (p)	0.90	0.32	0.06	0.71	0.05	0.89
Hansen (p)	0.85	0.64	0.07	0.38	0.23	0.54

Note: All specifications were estimated using a GMM first-difference specification. *m1 (m2)* is a test for first- (second-) order serial correlation in the first-differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation. The *Hansen* statistic is a test of the over-identifying restrictions, distributed as chi-square under the null of instrument validity. The instrument matrix includes the second and further lags of all regressors, time dummies and time dummies interacted with industry dummies. Uncertainty ($\sigma_{\ it}$) is computed as the 3-year moving standard deviation of the unpredictable part of sales. *, **, *** indicate significance at the 10%, 5% and 1% significance level, respectively. Also see Notes to Table 1.

Table 3. Indirect impact of uncertainty

	(1) BE	(2) FI	(3) FR	(4) IT	(5) PT	(6) ES
$\Delta\ I_{it-1}$	0.005	0.036	-0.025	0.010	-0.099**	0.007
	(0.042)	(0.054)	(0.020)	(0.024)	(0.048)	(0.028)
$\Delta\ S_{it}$	0.538**	0.752***	0.587***	0.204	0.531***	0.514***
	(0.229)	(0.188)	(0.111)	(0.198)	(0.196)	(0.176)
$\Delta\ S_{it-1}$	0.008	-0.086*	-0.033*	-0.018	-0.063	-0.032
	(0.036)	(0.051)	(0.020)	(0.017)	(0.055)	(0.030)
$I/S_{\ it-1}$	-0.739***	-0.930***	-0.623***	-0.645***	-0.644***	-0.742***
	(0.156)	(0.137)	(0.068)	(0.075)	(0.183)	(0.095)
$NTC_{\ it}$	0.103	0.201	-0.419**	-0.160	0.140	0.194
	(0.299)	(0.522)	(0.168)	(0.201)	(0.351)	(0.256)
$Debt_{\ it}$	0.559*	1.925	0.532***	0.440*	0.587	-0.076
	(0.304)	(1.287)	(0.176)	(0.266)	(0.372)	(0.320)
$Liquid_{\ it}$	0.305	-0.281	0.115	0.144	-0.991	-0.260
	(0.250)	(0.407)	(0.154)	(0.243)	(0.873)	(0.293)
$\sigma_{\ it}$	1.206***	1.028*	0.475**	1.025**	1.224**	0.987***
	(0.391)	(0.551)	(0.230)	(0.445)	(0.587)	(0.347)
$NTC*\sigma_{\ it}$	-2.489*	-5.191**	-0.494	-2.129**	-1.275	-2.402**
	(1.360)	(2.474)	(0.715)	(0.988)	(1.820)	(1.006)
$Debt*\sigma_{\ it}$	-1.515	-0.346	-0.120	-1.054	-2.595	-0.936
	(1.682)	(2.788)	(1.177)	(1.047)	(2.056)	(1.482)
$Liquid*\sigma_{\ it}$	-3.090**	-1.694	-1.492*	-1.879	-1.607	-0.890
	(1.229)	(1.454)	(0.765)	(1.405)	(3.966)	(1.370)
Observations	7194	2280	19344	25466	3699	13263
No of firms	1399	460	4001	5177	789	2756
m1 (p)	0.00	0.00	0.00	0.00	0.00	0.00
m2 (p)	0.97	0.55	0.05	0.61	0.11	0.88
Hansen (p)	0.50	0.53	0.39	0.14	0.31	0.69

Note: All specifications were estimated using a GMM first-difference specification. *m1 (m2)* is a test for first- (second-) order serial correlation in the first-differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation. The *Hansen* statistic is a test of the over-identifying restrictions, distributed as chi-square under the null of instrument validity. The instrument matrix includes the second and further lags of all regressors, time dummies and time dummies interacted with industry dummies. Uncertainty ($\sigma_{\ it}$) is computed as the 3-year moving standard deviation of the unpredictable part of sales. *, **, *** indicate significance at the 10%, 5% and 1% significance level, respectively. Also see Notes to Table 1.

Table 4. Uncertainty using all current and past errors

	(1) BE	(2) FI	(3) FR	(4) IT	(5) PT	(6) ES
ΔI_{it-1}	-0.033	0.001	-0.034	-0.010	-0.096*	-0.034
	(0.036)	(0.047)	(0.022)	(0.028)	(0.054)	(0.027)
ΔS_{it}	0.823***	0.822***	0.689***	0.112	0.461**	0.654***
	(0.221)	(0.153)	(0.124)	(0.240)	(0.235)	(0.192)
ΔS_{it-1}	0.026	-0.074	-0.025	-0.004	-0.034	-0.008
	(0.033)	(0.045)	(0.019)	(0.017)	(0.054)	(0.030)
I/S_{it-1}	-0.672***	-0.835***	-0.622***	-0.510***	-0.611***	-0.612***
	(0.122)	(0.110)	(0.073)	(0.076)	(0.206)	(0.089)
NTC_{it}	-0.145	-0.777**	-0.398**	-0.433**	-0.020	-0.155
	(0.235)	(0.350)	(0.167)	(0.196)	(0.303)	(0.221)
$Debt_{it}$	0.320	0.750	0.539***	0.054	0.140	-0.330
	(0.219)	(0.909)	(0.149)	(0.198)	(0.301)	(0.329)
$Liquid_{it}$	-0.071	-0.846***	-0.014	-0.137	-1.183	-0.449*
	(0.171)	(0.248)	(0.129)	(0.156)	(0.744)	(0.253)
σ_{it}	0.872***	0.232	0.302*	0.282	1.585**	0.693***
	(0.286)	(0.277)	(0.169)	(0.222)	(0.633)	(0.258)
Observations	7194	2280	19344	25466	3699	13263
No of firms	1399	460	4001	5177	789	2756
m1 (p)	0.00	0.00	0.00	0.00	0.00	0.00
m2 (p)	0.59	0.36	0.04	0.32	0.03	0.75
Hansen (p)	0.80	0.71	0.08	0.20	0.14	0.49

Note: All specifications were estimated using a GMM first-difference specification. *m1 (m2)* is a test for first- (second-) order serial correlation in the first-differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation. The *Hansen* statistic is a test of the over-identifying restrictions, distributed as chi-square under the null of instrument validity. The instrument matrix includes the second and further lags of all regressors, time dummies and time dummies interacted with industry dummies. Uncertainty (σ_{it}) is computed as the standard deviation of the unpredictable part of sales using all current and past residuals. *, **, *** indicate significance at the 10%, 5% and 1% significance level, respectively. Also see Notes to Table 1.

Table 5. Uncertainty using all current and past errors

	(1) BE	(2) FI	(3) FR	(4) IT	(5) PT	(6) ES
Δ I_{it-1}	-0.006	0.002	-0.036*	0.001	-0.090*	-0.032
	(0.043)	(0.056)	(0.020)	(0.024)	(0.048)	(0.026)
Δ S_{it}	0.466*	0.893***	0.673***	0.004	0.506**	0.665***
	(0.243)	(0.221)	(0.104)	(0.197)	(0.206)	(0.173)
Δ S_{it-1}	0.016	-0.064	-0.024	-0.005	-0.044	-0.009
	(0.036)	(0.055)	(0.019)	(0.017)	(0.051)	(0.029)
I/S $_{it-1}$	-0.650***	-0.896***	-0.609***	-0.515***	-0.658***	-0.619***
	(0.148)	(0.139)	(0.067)	(0.071)	(0.173)	(0.084)
NTC $_{it}$	0.114	0.692	-0.397**	-0.184	0.139	0.068
	(0.296)	(0.644)	(0.169)	(0.197)	(0.371)	(0.237)
Debt $_{it}$	0.433	2.609*	0.596***	0.060	0.221	-0.511
	(0.300)	(1.537)	(0.160)	(0.215)	(0.327)	(0.335)
Liquid $_{it}$	0.353	0.048	0.094	-0.045	-0.933	-0.521*
	(0.246)	(0.468)	(0.147)	(0.189)	(0.883)	(0.291)
σ_{it}	1.449***	1.981***	0.562**	0.827**	1.848***	0.714**
	(0.526)	(0.731)	(0.225)	(0.380)	(0.611)	(0.350)
NTC*σ_{it}	-2.397*	-6.793***	-0.394	-3.572**	-1.935	-1.981**
	(1.326)	(2.384)	(0.571)	(1.418)	(1.410)	(0.817)
Debt*σ_{it}	-0.373	-4.132	-0.407	0.213	-0.583	1.697
	(1.608)	(3.831)	(0.705)	(0.823)	(1.635)	(1.236)
Liquid*σ_{it}	-3.927***	-3.072*	-1.207**	-1.287	-0.846	0.059
	(1.473)	(1.798)	(0.589)	(0.803)	(3.540)	(1.099)
Observations	7194	2280	19344	25466	3699	13263
No of firms	1399	460	4001	5177	789	2756
m1 (p)	0.00	0.00	0.00	0.00	0.00	0.00
m2 (p)	0.74	0.58	0.03	0.28	0.03	0.82
Hansen (p)	0.72	0.84	0.36	0.20	0.27	0.70

Note: All specifications were estimated using a GMM first-difference specification. *m1 (m2)* is a test for first- (second-) order serial correlation in the first-differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation. The *Hansen* statistic is a test of the over-identifying restrictions, distributed as chi-square under the null of instrument validity. The instrument matrix includes the second and further lags of all regressors, time dummies and time dummies interacted with industry dummies. Uncertainty (σ_{it}) is computed as the standard deviation of the unpredictable part of sales using all current and past residuals. *, **, *** indicate significance at the 10%, 5% and 1% significance level, respectively. Also see Notes to Table 1.

Working Paper List 2010

Number	Author	Title
10/09	John Tsoukala and Hashmat Khan	Investment Shocks and the Comovement Problem
10/08	Kevin Lee and Kalvinder Shields	Decision-Making in Hard Times: What is a Recession, Why Do We Care and When Do We Know We Are in One?
10/07	Kevin Lee, Anthony Garratt and Kalvinder Shields	Measuring the Natural Output Gap Using Actual and Expected Output Data
10/06	Emmanuel Amissah, Spiros Bougheas and Rod Falvey	Financial Constraints, the Distribution of Wealth and International Trade
10/05	John Gathergood	The Social Dimension to the Consumer Bankruptcy Decision
10/04	John Gathergood	The Consumer Response to House Price Falls
10/03	Anindya Banerjee, Victor Bystrov and Paul Mizen	Interest rate Pass-Through in the Major European Economies - The Role of Expectations
10/02	Thomas A Lubik and Wing Teong Teo	Inventories, Inflation Dynamics and the New Keynesian Phillips Curve
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Working Paper List 2009

Number	Author	Title
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09/13	John Tsoukalas	Input and Output Inventories in the UK
09/12	Bert D'Espallier and Alessandra Guariglia	Does the Investment Opportunities Bias Affect the Investment-Cash Flow Sensitivities of Unlisted SMEs?
09/11	Alessandra Guariglia, Xiaoxuan Liu and Lina Song	Internal Finance and Growth: Microeconometric Evidence on Chinese Firms
09/10	Marta Aloi and Teresa Lloyd-Braga	National Labor Markets, International Factor Mobility and Macroeconomic Instability
09/09	Simona Mateut and Alessandra Guariglia	Inventory Investment, Global Engagement, and Financial Constraints in the UK: Evidence from Micro Data
09/08	Christos Koulovatianos, Charles Grant, Alex Michaelides, and Mario Padula	Evidence on the Insurance Effect of Redistributive Taxation
09/07	John Gathergood	Income Uncertainty, House Price Uncertainty and the Transition Into Home Ownership in the United Kingdom
09/06	Thomas A. Lubik and Wing Leong Teo	Inventories and Optimal Monetary Policy
09/05	John Tsoukalas	Time to Build Capital: Revisiting Investment-Cashflow Sensitivities
09/04	Marina-Eliza Spaliara	Do Financial Factors Affect The Capital-Labour Ratio: Evidence From UK Firm-Level Data
09/03	John Gathergood	Income Shocks, Mortgage Repayment Risk and Financial Distress Among UK Households
09/02	Richard Disney and John Gathergood	House Price Volatility and Household Indebtedness in the United States and the United Kingdom
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Working Paper List 2008

Number	Author	Title
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08/09	Simona Mateut, Spiros Bougheas and Paul Mizen	Corporate trade credit and inventories: New evidence of a tradeoff from accounts payable and receivable
08/08	Christos Koulovatianos, Leonard J. Mirman and Marc Santugini	Optimal Growth and Uncertainty: Learning
08/07	Christos Koulovatianos, Carsten Schröder and Ulrich Schmidt	Nonmarket Household Time and the Cost of Children
08/06	Christiane Baumeister, Eveline Durinck and Gert Peersman	Liquidity, Inflation and Asset Prices in a Time-Varying Framework for the Euro Area
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08/02	Paul Mizen and Serafeim Tsoukas	What Effect has Bond Market Development in Asia had on the Issue of Corporate Bonds
08/01	Paul Mizen and Serafeim Tsoukas	Modelling the Persistence of Credit Ratings When Firms Face Financial Constraints, Recessions and Credit Crunches

Working Paper List 2007

Number	Author	Title
07/11	Rob Carpenter and Alessandra Guariglia	Investment Behaviour, Observable Expectations, and Internal Funds: a comments on Cummins et al, AER (2006)
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Number	Author	Title
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06/03	Woojin Chung, Richard Disney, Carl Emmerson & Matthew Wakefield	Public Policy and Retirement Saving Incentives in the U.K.
06/02	Sarah Bridges & Richard Disney	Debt and Depression
06/01	Sarah Bridges, Richard Disney & John Gathergood	Housing Wealth and Household Indebtedness: Is There a 'Household Financial Accelerator'?

Working Paper List 2005

Number	Author	Title
05/02	Simona Mateut and Alessandra Guariglia	Credit channel, trade credit channel, and inventory investment: evidence from a panel of UK firms
05/01	Simona Mateut, Spiros Bougheas and Paul Mizen	Trade Credit, Bank Lending and Monetary Policy Transmission