Financing Constraints and Firm Inventory Investment: A Reexamination

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Abstract

This paper shows that small firms inventory investment is substantially more sensitive (relative to large firms) to cash flow than previously recognized. Consequently, the strength of financing constraints on inventory investment may have been understated.

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1. Introduction

Recent empirical studies document a significant role of credit conditions for the cyclical behavior of inventories, see e.g. Carpenter et al. (1994), Carpenter et al. (1998), Kashyap et al. (1994), and Gertler and Gilchrist (1994). A common feature in these studies is the homogeneity imposed on slope parameters. In other words, it is assumed that the data can be pooled and a meaningful average slope parameter can be estimated. Advances in the heterogeneous dynamic panel literature—Pesaran and Smith (1995) and Pesaran et al. (1996) —suggest that estimation and inference in dynamic panel models can be mis-leading when slope heterogeneity is neglected. Erroneously imposing homogeneity is likely to be a serious issue for the study of a short run phenomenon such as inventory investment where slope parameters capture short run dynamics.

This paper re-examines evidence from the U.S. manufacturing sector. Specifically, I investigate the consequences of ignoring slope heterogeneity for the cyclical behavior of inventories. The analysis suggests significant effects of slope heterogeneity on inventory responses for groupings of firms that proxy for capital market access. Inventory investment responds much more sharply to cash flow shocks for firms that belong to the small size class and this depends on the degree of slope heterogeneity.[1]

I utilize a VAR framework to calculate impulse responses of inventory investment to cash flow shocks under the null of homogeneity(using a fixed effects OLS estimator) and under the alternative of heterogeneity of slope coefficients (using the mean group estimator of Pesaran and Smith (1995)). I find that inventory investment is significantly more responsive to cash flow shocks for small relative to large firms under the mean group approach than under the fixed effects OLS approach. One quarter after the shock, an "extra" 84 percent of sensitivity (small relative to large firms) is lost

[1] Hsiao and Tahmiscioglu (1997) discuss a related result for fixed investment.

under the fixed effects OLS estimator. Over a year horizon the cumulative effect amounts to 61 percent. Given that the effects of cash flow shocks die out quickly, this result implies that these differences are economically important and that the strength of financing constraints on firm inventory investment could have been seriously understated in previous studies.

2. Data and econometric methodology

I utilize a panel of 385 manufacturing companies from Compustat's quarterly files for the period 1975:1 to 1995:4.[2] The data set is trimmed to protect results from outliers and to satisfy the large time series dimension that the mean group estimator requires.[3] Following previous studies I use firm size as a measure of capital market access and accordingly classify firms as small and large.[4] In the data set, the median small firm is around twenty times smaller than the median large firm, pays very few dividends (retention ratio=0.99), and holds sizable inventories (27 percent of assets). Moreover, inventories are on average around ten times quarterly cash flows, implying that these assets can be effective shock absorbers.

Inventory investment and cash flow are modeled as endogenous variables in a VAR context with minimal restrictions. This approach, recognizes the usual critique on the (questionable) exogeneity of cash flow in investment equations. Moreover, in the presence of financing constraints, real and financial decisions should be intertwined and this fact is encompassed in a VAR framework. The specification is as follows:

[2]The period chosen roughly corresponds to the period examined by Carpenter, Fazzari, Petersen (1994), Carpenter, Fazzari, Petersen (1998).

[3]Details in section 1 of the Appendix.

[4]The asset cutoff value equals 300 million. This cutoff results in a panel of 190 large firms and 195 small firms with an average of 65 quarterly observations for the regression variables. This is the cutoff used in Carpenter, Fazzari, Petersen (1994), Carpenter, Fazzari, Petersen (1998), Gertler and Gilchrist (1994). Results are also available for different cutoff values.

$$y_{it} = \mu_i + A_i y_{i,t-1} + B_i x_{it} + \varepsilon_{it} \tag{2.1}$$

where,

$$i = 1, 2, ..., N \quad and \quad t = 1, 2, ..., T$$

The vector of endogenous variables, y_{it} consists of cash flow and inventory investment, that is,

$$y_{it} = \begin{pmatrix} cf_{it} \\ ii_{it} \end{pmatrix}$$

The matrix of exogenous variables, $x_{it} = [x_{i1}, x_{i2}, ...x_{iT}]\prime$, that are included in (2.1) consists of three quarter time dummies, the lagged inventory stock, and contemporaneous and lagged sales. Exogenous variables serve as controls, and account for the accelerator, stock adjustment, and seasonal effects. The specification is a variant of the widely used inventory investment model (see Blinder and Maccini (1991)).

The $(2, 2)$ matrix of autoregressive coefficients A_i for firm i is defined as:

$$A_i = \begin{pmatrix} a_{11,i} & a_{12,i} \\ a_{21,i} & a_{22,i} \end{pmatrix}$$

The magnitude and shape of the impulse response functions, where the analysis focuses, depend crucially on these coefficients.

The mean group estimator allows coefficients and error variances to vary by firm—indexed by i—and estimates (2.1) separately for each firm. Pooled (or fixed effects) OLS by contrast, assumes that coefficients and error variances are homogeneous across firms, allowing only for firm specific fixed effects:

$$A_i = A, \quad B_i = B \qquad for \quad i = 1, 2, ...N \tag{2.2}$$

Table 1: Autoregressive Parameter Estimates

Small firms	Mean Group		Pooled OLS	
	a_{11}	a_{12}	a_{11}	a_{12}
Cash flow equation	0.59	-0.007	0.71	-0.013
	(0.015)	(0.0057)	(0.01)	(0.003)
	a_{21}	a_{22}	a_{21}	a_{22}
Inv.investment equation	0.16	0.062	0.10	0.079
	(0.03)	(0.014)	(0.015)	(0.011)
Large firms				
	a_{11}	a_{12}	a_{11}	a_{12}
Cash flow equation	0.69	0.1	0.79	-0.01
	(0.017)	(0.016)	(0.008)	(0.005)
	a_{21}	a_{22}	a_{21}	a_{22}
Inv.investment equation	0.069	0.002	0.052	0.094
	(0.013)	(0.015)	(0.009)	(0.01)

Standard errors in parenthesis.
Heteroskedasticity robust standard errors are reported for the OLS estimates.

Pooled OLS estimates,

$$y_{it} = \mu_i + Ay_{i,t-1} + Bx_{it} + \varepsilon_{it} \tag{2.3}$$

where μ_i is a fixed firm effect. Table 1 reports the estimated autoregressive parameters.

To test for heterogeneity I test assumption (2.2) plus homogeneity of error variances, ε_{it}. Using an F-test on the residuals of the unrestricted and the restricted models, equations (2.1) and (2.3) respectively, I obtain $F_{obs} = 433.6$ for large firms, and $F_{obs} = 271.6$ for small firms, both being significant at the 1 percent level. I verify this via a Haussman type test of the difference between the two estimators. Under the null of homogeneity, the test statistic $h \sim \chi^2_{k+1}$, where k= number of right hand side variables. The critical value with k=7 equals 18.48, which is smaller for both small and large firms values ($h^L_{ii} = 33.3, h^L_{cf} = 29.8$, $h^S_{ii} = 41.2, h^S_{cf} = 45.6$, where subscripts refer to VAR variables).[5]

3. Results

I compare the impulse responses of inventory investment for small and large firms that result from specifications (2.1) and (2.3). Figure 1 plots the difference between small firms and large firms controlling for cash flow shock size.[6] It is immediately evident that pooled OLS generates a bias in the small-large firm difference in inventory responses. In particular, one quarter after the shock (peak response), there is an 'excess' sensitivity of 84 percent not captured by the pooled model, equation (2.3). Two quarters out I obtain a 54 percent sensitivity that is lost from pooling.[7] Summing these biases over a year horizon I obtain a cumulative downward bias of 61 percent that the pooled model generates.[8]

Figure 2 reveals that most of the difference observed in Figure 1 is due to small firms inventory impulse responses that differ substantially across models (0.13 peak response in the MG model compared to 0.085 peak response in the OLS model one quarter out). In turn, this difference (at peak response) depends on the coefficient estimates of the inventory investment equation, that is, $\hat{a}_{21}^{i}$ and $\hat{a}_{22}^{i}$, $i = MG, OLS$. As can be seen from Table 1, for small firms, the difference $\hat{a}_{21}^{MG} - \hat{a}_{21}^{OLS}$ equals 0.06, while the difference $\hat{a}_{22}^{MG} - \hat{a}_{22}^{OLS}$ equals -0.017. Since the difference on the coefficient of lagged cash flow ($\hat{a}_{21}$) dominates, the effect of cash flow on inventory investment for small firms

[5]Details of these tests are given in Pesaran Smith and Im (1996) and Baltagi (2001).

[6]The impulse for all panels is a one standard deviation cash flow shock. For both the MG and the pooled OLS case, the impulse responses were calculated using the same matrix—of the standard deviations of the orthogonalized shocks—to minimize the impact of differences in cash flow shocks. In particular, I have used the small firms average orthogonalized shock matrix that result from the MG estimation, since the heterogeneous model is supported by the data. This implies that differences in impulse responses are entirely owed to differences in auto-regressive parameter estimates.

[7]As is evident from Figure 1 the bias declines with time. Three quarters out the downward bias reaches 24 percent.

[8]Section 4 of the Appendix presents impulse responses with 95 percent standard error bands and bias plots for different asset cutoff values.

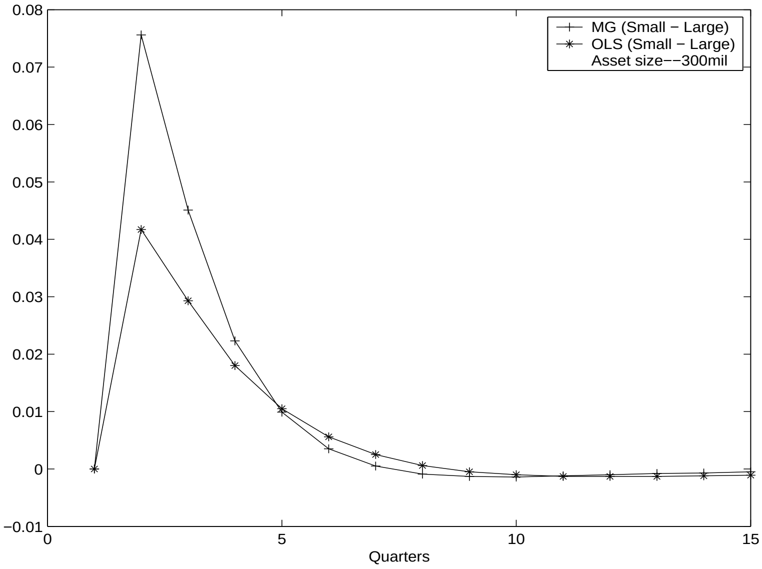
is underestimated by the pooled model relative to the MG model.[9] For large firms the size of the bias ($\hat{a}_{21}^{MG} - \hat{a}_{21}^{OLS}$) is much smaller (0.017) compared to small firms (0.06), whereas the bias ($\hat{a}_{22}^{MG} - \hat{a}_{22}^{OLS}$) is much larger (-0.092), and hence the difference at peak response is only marginal. As suggested in the introduction the observed biases should depend on parameter heterogeneity. The analytical and Monte Carlo results in Pesaran and Smith (1995) and Pesaran, Smith and Im (1996) show that the inconsistency (and finite sample bias) of any pooled method increases in the degree of heterogeneity and that it is always negative (downward) for the exogenous variable (cash flow) and positive (upward) for the lagged endogenous variable (inventory investment) in a single equation framework, as the results in Table 1 confirm. In order to get a sense of the magnitude of the heterogeneity in a_{21} I examine the distributions of the $\hat{a}_{21}^{MG}$ coefficients for small and large firms. The distribution of $\hat{a}_{21}^{MG}$ for small firms is much more dispersed around the mean relative to the corresponding distribution for large firms ($std_{small}^{\hat{a_{21}}}$=0.43, $std_{large}^{\hat{a_{21}}}$=0.21). Hence, the size of the biases in these coefficients are as theory predicts; the bias of $\hat{a}_{21}^{OLS}$ for small firms is larger compared to the bias of $\hat{a}_{21}^{OLS}$ for large firms.[10]

4. Conclusion

This paper highlights the consequences of ignoring parameter heterogeneity for the behavior of inventories. Employing the mean group estimator that preserves parameter heterogeneity, it is shown that small firms' inventory responses to cash flow shocks are significantly stronger relative to large firms than previously recognized.

[9] Section 3 of the Appendix calculates explicitly the bias at lag 1.
[10] Section 3 of the Appendix plots distributions of the mean group estimates.

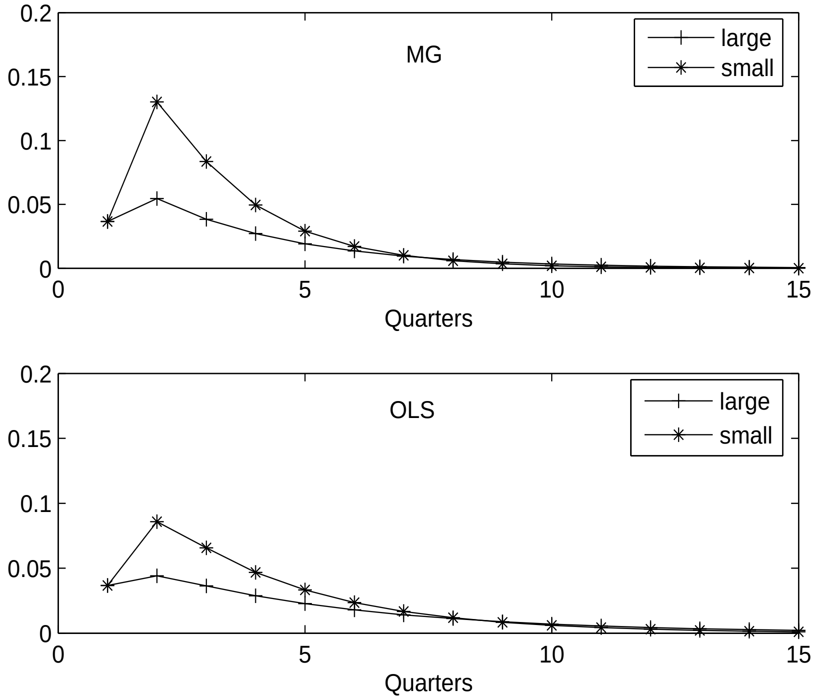
Figure 1: Impulse response of inventory investment



Recursive Ordering: Cash flow, Inventory investment

Unit standard deviation cash flow shock

Figure 2: Impulse response of inventory investment



Recursive Ordering: Cash flow, Inventory investment

Unit standard deviation cash flow shock

References

Baltagi, B., *Econometric Analysis of Panel Data*, John Wiley & Sons Ltd, West Sussex, England, 2001.

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

Carpenter, R., S. Fazzari, and B. Petersen, "Inventory (dis)Investment, Internal Finance Fluctuations and the Business Cycle," *Brookings Papers on Economic Activity*, 1994, *2*, 75–138.

_ , _ , and _ , "Financing Constraints and Inventory Investment: A Comparative Study With High Frequency Panel Data," *The Review of Economics and Statistics*, 1998, pp. 513–519.

Gertler, M. and S. Gilchrist, "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *Quarterly Journal of Economics*, 1994, *59*, 309–340.

Hsiao, C. and A.K. Tahmiscioglu, "A Panel Analysis of Liquidity Constraints and Firm Investment," *Journal of the American Statistical Association*, 1997, *92*, 455–465.

Kashyap, A., O. Lamont, and J. Stein, "Credit Conditions and the Cyclical Behavior of Inventories," *Quarterly Journal of Economics*, 1994, *109*, 565–592.

Pesaran, H.M. and R. Smith, "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels," *Journal of Econometrics*, 1995, *109*, 79–113.

_ , _ , and K.S Im, *The Econometrics of Panel Data: A Handbook of the Theory with Applications*, Kluwer Academic Publishers, Dordrecht, 1996.