Chapter 4 – Financing constraints, micro adjustment of capital demand and aggregate implications

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Abstract:

Following a positive shock, financing constraints will prolong or impede economic expansion that would have been optimal in an unconstrained environment. The study of dynamic adjustment therefore offers a direct way of verifying the presence of financing constraints and assessing their consequences for economic allocation.

This paper compares the speed of adjustment of constrained and unconstrained firms using categorical information from survey data on the restrictions under which adjustment takes place. A set of moment conditions for the use in GMM estimation is developed, to cope with the problem of time varying speed of adjustment when the target level is partially unobserved.

After estimating the micro-dynamics of capital demand, I show that the changing composition of the population makes for a time-varying sensitivity of the aggregate with respect to macroeconomic shocks.

Keywords: Financing constraints, adjustment, dynamic panel data models

JEL-Classification: C23, D21, D24

Financing constraints, micro adjustment of capital demand and aggregate implications

1 Introduction

With informational frictions, indivisibilities and irreversibilities, the reaction of aggregate factor demand to aggregate shocks will not be time-invariant. Instead, it will depend on the distribution of individuals in the relevant state-space. In a prototypical (S,s) model of irreversible investment, a region of inaction is bounded by an upper and a lower threshold that triggers investment and hiring, or disinvestment and firing.[1] The individual reaction to measures of fundamentals will be nonlinear: investment bursts (spikes) will be followed by relative inaction. On the aggregate level, the reaction to a positive shock will be sharp if a large mass of individual agents is situated near the upper threshold, as opposed to a situation where a series of negative shocks has driven agents to the edge of disinvestment.[2] Models of informational asymmetry describe a similar range of inactivity for individuals. If the market value of their assets is insufficient to sustain externally financed expansion, firms will not be able to make use of profitable investment opportunities, or have to take the slow lane of accumulation by internal finance. Again, the sensitivity of aggregate factor demand to productivity or demand shocks and user cost changes induced by tax reforms or monetary policy will depend on the distribution of equity or liquidity ratios among firms, as induced by recent history. The action of the financial accelerator is quite asymmetric in booms and busts.[3] This "asymmetry", as we may call the state dependence of correlations between macroeconomic aggregates and prices, is important for policy makers as well as for market participants, forecasters and analysts.

In such a situation, there is a high value attached to direct information on the position of individuals in state space that would allow us to infer the aggregate sensitivity. This paper argues that survey data can be a timely and informative source of information

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1 Abel and Eberly (1996), Abel, Dixit, Eberly and Pindyck (1996), Bentolila and Bertola (1990).
2 Caballero, Engel and Haltiwanger (1995, 1999).
3 See Bernanke and Gertler (1989, 1995) and Bernanke, Gertler and Gilchrist (1996, 1999) on the credit channel and the financial accelerator.

about the relevant constraints for individuals. More specifically, it deals with financing constraints at the firm level and their effect on the aggregate.

I argue first that the most important real effect of financing constraints is to slow down the adjustment of capital and labour input to positive, expansionary shocks (Section 2). In explicitly relating financing constraints to the adjustment dynamics, our paper is related to Basu and Guariglia (2002) and Bayer (2006). I then lay out a GMM based technique to estimate micro level adjustment equations when the target is unobserved and the adjustment speed varies over time, and categorical information on adjustment regimes is available (Section 3). This estimation technique is developed in Chapter 3, and it has a wide range of applications for other important adjustment processes, such as sales price adjustment by firms, interest pass through by banks or the adjustment of equity ratios. The specific empirical strategy for the problem at hand is developed in Section (4). Section (5) takes the estimation technique to the data, using micro data from a survey on the investment behaviour of German industrial companies (the Ifo *Investitionstest*). Adjustment functions for the real capital stock are estimated. These estimates show that regime specific dynamic behaviour can successfully be disentangled. We see that – as hypothesized – financing constraints slow down the speed of adjustment of firms. Furthermore, this effect is concentrated on or perhaps even limited to smaller firms. With large firms, no clear speed differential can be detected. Ultimately we see that the speed of adjustment of small firms is clearly higher than for large firms. The results fit extremely well to what was obtained in Chapter 2 for capacity adjustment of UK firms, using an entirely different methodology on a different type of data, even quantitatively.

In a last step, some of the aggregate implications are worked out (Section 6). The aggregate sensitivity changes with the composition of the aggregate. With estimated adjustment functions in hand, it is easy to trace the time-varying aggregate sensitivity. This offers an important new way in which survey data can be used by analysts and forecasters.

2 Financing constraints and investment dynamics

Empirical work on financing constraints has traditionally been based on an approach pioneered by Fazzari, Hubbard and Peterson (1988). They divide their sample into constrained and unconstrained firms using ad hoc criteria. If the investment of financially constrained firms shows a higher sensitivity to internal finance than the investment of their unconstrained counterparts, this is seen as evidence for the existence of binding financial constraints. In recent years, this approach has been forcefully criticised. Kaplan and Zingales (1997) state that there is no theoretical reason why – in a comparison between firms – a larger cost differential between internal and external finance might lead to a higher cash-flow sensitivity, as opposed to just comparing the extreme cases of a constrained firm and an absolutely unconstrained one. A non-monotonic relationship between the cost differential and excess sensitivity is perfectly conceivable.[4] On the other hand, it has been shown theoretically that, under certain conditions, cash flow terms can be significant even in the absence of financing constraints.[5] Ultimately, there is a pervasive missing variable problem. Cash flow is a close relative to profit, a summary measure of all that is important for a firm, and it is useful in predicting future values of variables relevant to the current investment decision.[6]

Here, we use a direct approach by relying on explicit statements by the firms themselves. We are able to explore the micro data base of the Ifo institute's *Investitionstest* (Investment Test, IT) for the manufacturing sector in West Germany during the years 1988 to 1998. During these eleven years, the autumn wave of the survey yields 25,643 observations on a total of 4,443 firms, with 2,331 firms per year on average. Apart from its size and coverage, the data set has two important characteristics that are relevant to our problem. First, it contains many small firms, on which very little information is available in data sets based on quoted companies. Although large firms are clearly oversampled, almost one half of the IT observations refer to firms with fewer than 200 employees, and around 20% of the firms have fewer than 50 employees. Second, the data set contains information on financing constraints that firms face in their investment de-

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4 The discussion was continued in Fazzari, Hubbard and Peterson (2000) and Kaplan and Zingales (2000).

5 See the models by Abel and Eberly (2003), Cooper and Ejarque (2001), and Gomes (2001).

cisions. Notably, a number of firms (around one quarter of respondents) explicitly state that their investment demand is limited by the cost and/or the unavailability of finance. Although part of this may be due to the workings of the classical interest rate channel, these aggregate effects can be eliminated by the use of time dummies, focussing on differential changes in time.

Chapter 1 argues that a specific pattern with respect to the distribution of investment over time should be expected to hold for financially constrained firms. Given a shock, an unconstrained investor can adapt rapidly or even instantaneously if other types of adjustment costs are unimportant. The bulk of investment spending will take place in the first few periods, and there may be a spike in the first period. If the investor is financially constrained, however, marginal costs of finance will increase with the amount of spending, possibly to infinity. In such a setting, the investor has to equalise marginal costs of finance and the marginal value of new investment in each period. After an initial debt-financed increase in the capital stock that leads to a worsening of the financial position, the firm needs internal finance to continue the expansion and to repair balance sheets gradually. Thus, the adjustment will be spread over time. This crucial difference in the adjustment dynamics can be used to identify financially constrained firms, or better, to test whether a subset of supposedly constrained firms really is, without having to take recourse to cash flow sensitivities. The hypothesis is examined empirically in Chapter 2, using set of survey data on UK firms with entirely qualitative information. The duration of capacity restrictions is compared between firms that characterised themselves as being financially constrained, and others that did not.

The Ifo Investment Test has a different and more specific informational content, in that many key variables are continuously scaled, so that the adjustment dynamics can be much more closely observed. Chapter 2 proceeds to sort firms into two groups, according to whether they are predominantly financially constrained or not. This approach has a serious drawback: it does not make use of the time variation in the financing constraints variable for a given firm.[7] This is most valuable in micro-econometrics, when many important aspects of the process in question are unobserved, but can be trusted to

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[6] This argument is developed formally in Appendix B of Chirinko and von Kalckreuth (2002).
[7] I thank John van Reenen for making this point. Doing so, he set me on the track that led to this paper.

be relatively stable in time. It is the variation in the left hand variable following a variation of the explanatory variable that helps to identify structural relationships. However, a time varying adjustment coefficient poses special problems if the target is unobserved. These will be discussed in the next section.

The interrelation of financing constraints and investment behaviour is studied also by Basu and Guariglia (2002), looking at the dynamics of capital returns. Our approach is closest in spirit to Bayer (2006). In this paper, a gap model of adjustment is estimated, where capital imbalances are measured as an imputed difference between capital stock and imputed target, whereas financing constraints are proxied simply using the equity ratio. For both of these fundamental magnitudes, a treatment of unobserved differences between firms is extremely difficult. Therefore, the empirical approach presented next may greatly alleviate some of these measurement problems.

3 State dependent adjustment dynamics with unobserved targets

This section draws on Chapter 3, a companion paper that studies moment conditions that can be used in the estimation of an adjustment model with unobserved target and time-varying speed of adjustment in a context of panel data. The econometric method is tailor-made for the problem at hand, but has considerably more general use.

In a rather general form, economic adjustment can be framed by a "gap equation", as formalised by Caballero, Engel and Haltiwanger (1995):

$$\Delta y_{i,t} = \Lambda\left(x_{i,t}, \mathbf{z}_{i,t}\right) \cdot x_{i,t}, \text{ where} \qquad x_{i,t} = y_{i,t-1} - y^*_{i,t}.$$

Here, subscripts refer to individual i at time t, and $x_{i,t}$ is the gap between the state $y_{i,t-1}$ inherited from the last period and the target $y^*_{i,t}$ that would be realised if adjustment costs were zero for one period of time. The speed of adjustment, written as a function Λ of the gap itself and additional state variables $\mathbf{z}_{i,t}$, determines the fraction of the gap that is removed within one period of time. The adjustment function reflects convex or non-convex adjustment costs, irreversibility and indivisibilities, financing constraints or other restrictions, and the uncertainty of expectation formation. With quadratic adjustment costs or Calvo-type probabilistic adjustment, Λ will be a constant.

Estimating the function Λ is inherently difficult. In general, both $y^*_{i,t}$ and $x_{i,t}$ are not observable. However, some measure of the gap is needed for estimation, and if Λ explicitly depends on $x_{i,t}$, the measure moves to the centre stage.

In linear dynamic panel estimation, this problem can successfully be addressed by positing an error component structure for the measurement error and eliminating the individual fixed effect by a suitable transformation, such as first differencing. See Bond et al. (2003) and Bond and Lombardi (2007) for an error correction model of capital stock adjustment. The GMM estimator developed by Arellano and Bond (1991) accounts for the presence of lagged endogenous variables, the endogeneity of other explanatory variables, and unobserved individual specific effects. Individual effects (including a possible measurement error in the target) are differenced out. Endogenous explanatory variables can be instrumented using lagged dependent variables if serial correlation of the error process is limited. Time fixed effects can also be accommodated; the remaining idiosyncratic component of the measurement error needs to be uncorrelated with the instruments.

In the unrestricted, non-linear case, this approach is not feasible, as a host of incidental parameters will threaten identification. But there may be direct qualitative information on the level of $\Lambda(\ )$, e.g. from survey data, ratings or market information services. If one is willing to treat the adjustment process as piecewise linear, distinguishing regimes of adjustment, then this information can be harnessed to eliminate the incidental parameters from the problem completely.

3.1 The estimation problem

I examine a situation where a variable $y_{i,t}$ reverts to some target level $y^*_{i,t}$ characteristic of individual *i*. The speed of adjustment depends on the value of $\mathbf{r}_{i,t}$. This is an *L*-dimensional column vector of regime indicator variables, with one element taking a value of 1, and all others being zero. The equation is:

$$\Delta y_{i,t} = -\left(1-\alpha_{i,t-1}\right)\left(y_{i,t-1} - y^*_{i,t}\right) + \varepsilon_{i,t} \ ,$$

with

$$\alpha_{i,t} = \boldsymbol{\alpha}'\mathbf{r}_{i,t} .$$

The target level $y^*_{i,t}$ is unobservable. It follows an equation that contains an individual-specific latent term:

$$y^*_{i,t} = \mathbf{x}'_{i,t}\boldsymbol{\beta} + \mu_i .$$

The vector $\mathbf{x}_{i,t}$ may encompass random explanatory variables, deterministic time trends and also time dummies. In its absence, the target level is entirely unobservable, but static. The idiosyncratic component μ_i in the adjustment equation may reflect a measurement error or unobserved explanatory variables. Vector $\boldsymbol{\alpha}$ holds the state dependent adjustment coefficients. The adjustment coefficient $\alpha_{i,t}$ varies over time and individuals, and $\left(1-\alpha_{i,t-1}\right)$ is the adjustment speed at date *t*. The regime variable $\mathbf{r}_{i,t}$ is generated by a threshold process:

$$\mathbf{r}(k)_{i,t} = \mathrm{Ind}\left(c_{k-1} \le s_{i,t} \le c_k\right) .$$

with $s_{i,t}$ some latent variable. In general, a non-zero covariance between the error term and the regime indicators, $\mathrm{cov}\left(\varepsilon_{i,t}, \mathbf{r}_{i,t}\right) \neq 0$ can be expected. However, we assume that $\alpha_{i,t-1} = \boldsymbol{\alpha}'\mathbf{r}_{i,t-1}$ is predetermined with respect to $\varepsilon_{i,t}$, or more exactly:

$$\mathrm{E}\left(\varepsilon_{i,t} \middle| \mathbf{r}_{i,t-1}, \mathbf{r}_{i,t-2}, \ldots, \mathbf{x}_{i,t-k}, \mathbf{x}_{i,t-k-1}, \ldots, \varepsilon_{i,t-k-1}, \varepsilon_{i,t-k-2}, \ldots, \mu_i, y_{0i}\right) = 0$$

for some $k \in \{1, 2, \ldots\}$.

As we do not observe the target, we have no direct information on the position of the individual relative to the target. But the panel dimension can help us to identify the adjustment process nonetheless, as it allows us to use an error component approach for modelling the unobserved target. In the adjustment equation, both the individual effect and $\mathbf{x}_{i,t}$ are interacted with a time varying and endogenous variable.

3.2 A non-linear transformation

Solving for $y_{i,t}$ yields:

$$y_{i,t} = \alpha_{i,t-1} y_{i,t-1} + \left(1-\alpha_{i,t-1}\right) \mathbf{x}'_{i,t} \boldsymbol{\beta} + \underbrace{\left(1-\alpha_{i,t-1}\right) \mu_i + \varepsilon_{i,t}}_{\text{latent process}} . \qquad (1)$$

It is easily seen that, unlike the case of the standard linear dynamic panel model, first differencing will not remove the latent fixed effect μ_i from the equation:

$$\Delta y_{i,t} = \boldsymbol{\alpha}' \Delta\left(\mathbf{r}_{i,t-1} y_{i,t-1}\right) + \Delta\left[\left(1-\alpha_{i,t-1}\right) \mathbf{x}'_{i,t}\right] \boldsymbol{\beta} \underbrace{+\left(\mathbf{1}-\boldsymbol{\alpha}'\right) \Delta\left(\mathbf{r}_{i,t-1} \mu_i\right) + \Delta \varepsilon_{i,t}}_{\text{latent process}} .$$

Chapter 3 develops a nonlinear transformation that eliminates the unobserved heterogeneity. Holtz-Eakin, Newey and Rosen (1988) propose quasi-differencing as a strategy in a case where fixed effects are subject to time varying shocks that are common across individuals.[8] Their method can be modified and generalised to the case at hand, where coefficients are endogenous and vary over time and individuals. Multiplying equation (1) by $\left(1-\alpha_{i,t-2}\right) / \left(1-\alpha_{i,t-1}\right)$ and subtracting the lag of the original adjustment equation leads to

$$\frac{1-\alpha_{i,t-2}}{1-\alpha_{i,t-1}} \Delta y_{i,t} - \alpha_{i,t-2} \Delta y_{i,t-1} - \left(1-\alpha_{i,t-2}\right) \Delta \mathbf{x}'_{i,t} \boldsymbol{\beta} = \xi_{i,t} ,$$

with

$$\xi_{i,t} = \frac{1-\alpha_{i,t-2}}{1-\alpha_{i,t-1}} \varepsilon_{i,t} - \varepsilon_{i,t-1} .$$

The unobserved heterogeneity μ_i has been eliminated.[9] Let $\mathbf{d}\left(\mathbf{r}_{i,t-2}, \mathbf{r}_{i,t-1}\right)$ be an $L^2 \times 1$ indicator vector, where each element is a dummy variable indicating one of the possible switches from $\mathbf{r}_{i,t-2}$ to $\mathbf{r}_{i,t-1}$. Let $\boldsymbol{\lambda}$ be the vector of coefficients $\left(1-\alpha_{i,t-2}\right) / \left(1-\alpha_{i,t-1}\right)$ corresponding to the elements of $\mathbf{d}(\cdot)$:

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8 See also Chamberlain (1983), p. 1263-64.

9 Applied to the current problem, the quasi-differencing transformation proposed by Holtz-Eakin, Newey and Rosen lags equation (1), multiplies both sides by $\left(1-\alpha_{i,t-1}\right) / \left(1-\alpha_{i,t-2}\right)$ and subtracts the result from equation (1). Although this eliminate the fixed effect, in the given context the transformed error term $\varepsilon_{i,t} - \left(1-\alpha_{i,t-1}\right) / \left(1-\alpha_{i,t-2}\right) \varepsilon_{i,t-1}$ is unsuitable for estimation, as $\alpha_{i,t-1}$ and $\varepsilon_{i,t-1}$ will be correlated in general. Chapter 3 discusses three additional sets of useful moment conditions.

$$\boldsymbol{\lambda}' = \begin{pmatrix} 1 & \frac{1-\alpha_1}{1-\alpha_2} & \frac{1-\alpha_1}{1-\alpha_3} & \cdots & \cdots & \frac{1-\alpha_L}{1-\alpha_{L-2}} & \frac{1-\alpha_L}{1-\alpha_{L-1}} & 1 \end{pmatrix}.$$

Let ultimately $\boldsymbol{\delta}$ be a vector of products of the adjustment coefficients, $(\mathbf{1}-\boldsymbol{\alpha})$, and $\boldsymbol{\beta}$:

$$\boldsymbol{\delta} = (\mathbf{1}-\boldsymbol{\alpha}) \otimes \boldsymbol{\beta} = \begin{pmatrix} (1-\alpha_1)\boldsymbol{\beta} \\ (1-\alpha_2)\boldsymbol{\beta} \\ \vdots \\ (1-\alpha_L)\boldsymbol{\beta} \end{pmatrix}.$$

Then we can write:

$$\xi_{i,t} = \boldsymbol{\lambda}'\mathbf{d}\left(\mathbf{r}_{i,t-2}, \mathbf{r}_{i,t-1}\right)\Delta y_{i,t} - \boldsymbol{\alpha}'\mathbf{r}_{i,t-2}\Delta y_{i,t-1} - \boldsymbol{\delta}'\mathbf{r}_{i,t-2}\Delta \mathbf{x}_{i,t}. \tag{2}$$

This equation is linear in the transformed variables, but nonlinear in the unknown parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. In the companion paper, it is shown that levels $y_{i,t-p-k}$ and $\mathbf{x}_{i,t-p-k}$, as well as regime indicators $\mathbf{r}_{i,t-p-1}$, $p = \{1, 2, \ldots\}$ are instruments in equation (2), i.e. the following moment conditions are available for the identification of the unknown parameters:

$$\mathrm{E}\left(y_{i,t-p-k}\xi_{i,t}\right) = \mathrm{E}\left(\mathbf{x}_{i,t-p-k}\xi_{i,t}\right) = \mathrm{E}\left(\mathbf{r}_{i,t-p-1}\xi_{i,t}\right) = \mathbf{0}.$$

The paper describes in detail how GMM estimation of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ is to be implemented, using Gauss-Newton iterations to deal with the nonlinearities involved.

4 Empirical strategy

Following the gap approach, I formulate the econometric model as a partial adjustment mechanism. The model is a special case of the error correction factor demand equation invented by Charles Bean (1981), and introduced to the micro literature by Bond, Elston, Mairesse and Mulkay (2003).[10] A full blown ECM that would also take transitory dynamics into account could in principle be estimated as well, see Chapter 3, Appendix A. In practice it is difficult to separately identify transitory dynamics and overall adjustment speed if all coefficients are regime specific.

[10] See Chapter 1, Appendix B for a detailed discussion of the capital demand ECM.

The point of departure is the static neoclassical equation for factor demand. Using a constant returns CES production function, the following linear equation for capital results from the first-order conditions of profit maximisation:

$$\log K_t^* = \log Y_t^* - \sigma \log UC_t^* + \log h_t^*,$$

where K_t is capital, Y_t is real output, UC_t is the user costs of capital, σ is the elasticity of substitution, and h_t is a magnitude that depends on technology parameters and the time varying total factor productivity. A star denotes a long-run, equilibrium value. We may model adjustment by replacing the starred values by observed quantities:

$$\log K_{i,t}^* = \log S_{i,t} + \lambda_t + \mu_i \tag{3}$$

Here, λ_t is a time fixed effect that catches the effect of user cost changes, time varying total factor productivity and other macro disturbances and will be estimated using a full set of time dummies. The firm fixed effect μ_i will catch the unobserved firm specific technological determinants for capital intensity. The log of real sales, $\log S_{i,t}$ will be our proxy for variations in real output. Depending on the usage of intermediate products as inputs, real sales and real output will differ, but to the degree that the share of intermediates in output is a firm specific constant underlying a common trend equation, equation (3) still holds. Assuming that the speed of adjustment may vary with financing conditions, we arrive at the following adjustment equation:

$$\Delta \log K_{i,t} = -\phi\left(\mathbf{r}_{i,t-1}\right)\left(\log K_{i,t-1} - \log S_{i,t} - \lambda_t - \mu_i\right) + \varepsilon_{i,t}, \tag{4}$$

with

$$\phi\left(\mathbf{r}_{i,t-1}\right) = 1 - \alpha_{i,t-1} = 1 - \boldsymbol{\alpha}'\mathbf{r}_{i,t}$$

where $\phi\left(\mathbf{r}_{i,t-1}\right)$ is the time varying, regime specific speed of adjustment and $\alpha_{i,t-1}$ is a measure of regime specific persistence. In a subset of estimates, the target equation (3) – and the expression in brackets in equation (4) – will be augmented by

$$\omega_{i,t} = \boldsymbol{\omega}'\mathbf{z}_{i,t}, \tag{5}$$

with $\mathbf{z}_{i,t}$ a vector of indicators for the levels of the sales conditions in period *t*, and $\omega_{i,t}$ thus giving additional information on the level of the capital stock target.

Question 5 [Autumn survey]: Factors influencing investment in 1999-2000

In 1999-2000 our investment in western Germany was/is being positively/adversely affected by the following factors: (Please refer to the explanatory notes on the reverse of the accompanying letter.)

	1999					2000				
Factors	Very stimu-lating	Stimu-lating	No influ-ence	Lim-iting	Very limi-ting	Very stimu-lating	Stimu-lating	No influ-ence	Lim-iting	Very limi-ting
Sales conditions / expectations										
Availability / costs of finance										
Earnings expectations										
Technical develop-ment										
Acceptance of new technologies										
Basic economic policy conditions										
Other factors, namely ...										

The Ifo data set and its information on investment and financing conditions have been discussed in detail in Chapter 1. In order to generate regime indicators, I use Question 5 of the autumn survey, which asks for factors stimulating or limiting investment in the current year and in the coming year. Both sets of answers are utilised.

I generate three different sets of regime indicators. In the data sets, the factors for investment may take one of five values. Our first regime partition, R(1), is defined straightforwardly using the values of the financing factor for realised investment in Question 5. This regime indicator comes very natural and therefore its results will be suggestive. However, it has two drawbacks. First, testing the significance of financing constraints becomes difficult if there are as much as five different regimes. Therefore, a second indicator, R(2) distinguishes only three regimes, by aggregating the categories "very stimulating" and "stimulating" to one regime, and "limiting" and "very limiting" to another.

A potential problem with R(1), shared by R(2), is the requirement of regime information to be predetermined. A shock to the investment equation – a large value of $\varepsilon_{i,t}$ – may lead to financing needs that may themselves bring about a worsening of financial conditions. Endogeneity is no problem if firms identify financing conditions in a way that abstracts from current financing needs, but this is hard to verify. I therefore define a third regime partition, R(3), on the basis of factors related to *expected* investment – the right hand set of categories in Question 5 – lagged one year. The statement on financing conditions thus antedates actual investment expenditure by about one year.[11]

The regime partition R(3) also deals with another issue. The theoretical argument on financing constraints and the speed of adjustment relate to firms having to finance positive investment expenditures, either expanding the firm or restructuring the capital stock in order to cope with a changing economic environment. It is not clear what is to be expected from firms that aim at downsizing. Furthermore, as has been stated above, the adjustment speed for rapidly downsizing firms may be mismeasured anyway. Therefore R(3) distinguishes three regimes: first, stationary or expanding forms that are financially unconstrained, second, stationary or expanding firms that are financially constrained and third, potentially downsizing firms. The latter category encompasses those firms that state "limiting" or "very limiting" sales conditions for the investment of the following year. Among the rest, financially constrained firms are those that state their expected financing situation as either "limiting" or "very limiting". The empirical analysis will focus on the first two regimes, comparing financially constrained and unconstrained episodes in the group of stationary of expanding firm-years.

For each regime partition, I will perform estimation using all firms, and also separately for firms with 199 employees and less (small firms) and for firms with 200 employees or more (large firms). This is done, because the investigation in Chapter 2, using a duration model on qualitative data from a UK data set, has shown clear differences between the effect of financing constraints on the firm dynamics according to firm size.

[11] Some remaining endogeneity of R(3) cannot be excluded. Chapter 3 describes an estimator that can cope with fully endogenous regime information. However, this alternative estimator, among other things, necessitates the firm fixed effect μ_i to be uncorrelated with all $\mathbf{r}_{i,t}$ and $\Delta\mathbf{x}_{i,t}$, past and present, as well as with the initial deviation. In the current context, this would be a rather strong assumption.

Such differences may be related to large firms being able to choose among a broader set of financing opportunities.

Each estimation is done with and without the additional sales indicators in the capital stock target equation, see equations (3) and (5). These indicator variables are invariably generated on the basis of current *realised* investment factors, because the GMM approach adequately deals with the endogeneity of standard explanatory variables, as opposed to the above mentioned requirements concerning regime partition information.

5 Descriptive statistics and estimation results

Table 1 gives the descriptive statistics for the continuous model variables: $\log K_{i,t}$, $\Delta \log K_{i,t}$, $\log S_{i,t}$, and $\Delta \log S_{i,t}$, in the cleaned dataset of firms where at least three consecutive firm-years are available. That many lags are needed to yield just one valid observation in a first difference Arellano-Bond (1991) estimation of the adjustment equation, if a uniform speed of adjustment is assumed and equation (4) can be written as a standard AR(1) with fixed effects. The breakdown of the standard deviation demonstrates that ample within-firm variation is present, as far as changes $\Delta \log K_{i,t}$ and $\Delta \log S_{i,t}$ are concerned.

Table 2 gives a breakdown of these same variables according to size classes. It shows the large number of small firms in the dataset: the two lesser size categories hold about the same number of firms than the two larger size classes, encompassing firms with 200 employees and more. Size, both in the table and in the estimations, is measured at the beginning of an uninterrupted string of observations in the cleaned sample, in order to exclude endogeneity in the classification. It has to be noted that the Ifo institute splits some of the very largest companies up into smaller sub-units if business activities, investment and markets can be analysed separately. These entities receive separate questionnaires. Therefore, the distinction between small and large firms may at times be blurred: firm size measures the number of employees in an organisational entity that does not always coincide with a legal entity.[12]

Table 3 gives an overview of the distribution for the financing conditions and the sales conditions variables generated by the question on factors for realised investment. It has been noted above that these two variables are underlying regime partition R(1) and the additional sales conditions indicator $\omega_{i,t} = \boldsymbol{\omega}'\mathbf{z}_{i,t}$, respectively. The number of observations in Table 3 is smaller than in Table 1 for a variety of reasons. First, the question on investment factors was asked only from autumn 1989 on. Still, the capital stock and sales data from spring 1988 are kept in the data set in order to generate necessary lags and first differences. Furthermore, not every observation on sales and capital stocks from the spring survey can be matched to an observation of the preceding autumn survey that yields the investment factors. Ultimately, about one tenth of respondents in the autumn survey do not give information on investment factors, as this is not required by the Ifo institute. In about half of these cases, no information on any factor is given. Often, this coincides with no investment being planned or having been undertaken. In the other 47% of cases were financing conditions information is missing, the sales indicator is present. This may be considered a source of selectivity, but it may also simply be due to the fact that not all firms are independent legal entities.

Using the fact that Question 5 is asked for two consecutive years, I have imputed missing data on investment factors from observations in adjacent years, wherever possible, in order to mitigate selectivity problems. Missing data in the autumn 1988 wave, where the question was not yet asked, were not imputed.

In Table 3, *overall* percentages summarise results in terms of firm-years. The distribution of financing conditions shows that "very stimulating" (3.6%) and "very limiting" (7.3%) episodes are relatively rare. In almost 60% of episodes, finance is considered "neutral". A share of 23.5% of firm-years are characterised by financing constraints, with financing conditions being "limiting" or "very limiting". The *between* columns repeat the breakdown in terms of observational units, giving the percentage of firms that ever had a specified value. Obviously, the percentages add up to more than 100, as

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[12] Due to confidentiality reasons, the units that are part of a larger conglomerate are not separately identi-

many firms' responses vary over time. The *within* columns show this variation from a different perspective, giving the fraction of times firms report a certain value, conditional on that value being reported at last once. A time invariant categorical variable would be characterised by a value of 100% in each *within* entry.

As mentioned in the beginning, our estimator is specifically designed to make use of the within variation in regime information. Therefore Tables 4 and 5 give the transition matrices for the two regime partitions that may take three values, R(2) and R(3). Looking first at Table 4 featuring the three-level financing conditions indicator, we see that the regimes are moderately persistent: all three values are followed by the same value in more than 50% of cases. In both the first (stimulating or very stimulating) and the third (limiting or very limiting) categorise, also the off-diagonal elements are well filled, whereas the "neutral" category is followed by another value in only 20% of cases. A different picture results for the case of R(3) from Table 5. Whereas 72% of the unconstrained expanders are unconstrained expanders also in the next period, it is only 41% of the constrained expanders who find themselves in the same regime also in the next period. The rest defects with about the same probability to the first (unconstrained expanders) and the third regime (potential contractors). This clearly shows that a lot of noise would be introduced by fixing firm specific characteristics once and for all, not making use of within variation.

We now turn to Tables 6, 7 and 8 that hold the GMM estimations of the quasi-differenced adjustment equations. The tables all follow the same basic design. The first two columns hold the results for estimations that use the entire sample ("all firms"). In Column (1), the target equation for the capital stock is given by equation (3) without further modifications. In Column (2), the target equation is augmented by dummies from the sales conditions indicator. Columns (3) and (4) hold the results for small firms, with 199 employees or less, again with and without augmenting the target equation by sales condition information. Finally, Columns (5) and (6) report the results for large firms, with 200 employees or more, again using two specifications for the target equation. The set of instruments is uniform over tables and was defined on the basis of prior specification search using an Arellano-Bond (1991) first difference estimator on a model with homo-

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fied in the data set.

geneous adjustment speed. I use lags 1-6 of regime dummies, lags 3-6 of $\log S_{i,t}$ and $\log K_{i,t}$ and time dummies. In addition, lags 2-6 of sales conditions dummies are used for the estimates with the enlarged target equation, Columns (2), (4) and (6) of each table.

Table 6 reports the results for Regime partition R(1) that derives directly from the financing factor for realised investment. The tables report the alpha values, which are equal to 1 minus the speed of adjustment. With one marginal exception in Column (1), specifications tests do not reject the set of instruments. The Sargan-Hansen statistics of overidentifying restrictions are innocent and the LM(k) test on residual autocorrelation confirm that using as instruments the lags three and earlier of the capital stock and real sales variables is justified.

In all six columns, we see clearly that measured adjustment speed is decreasing when reported financing conditions get worse, although in some of the estimates there is an inversion for α_4 (finance limiting). In the regression without additional variables in the target equation, the measured adjustment speed in the estimations for the "all firms" sample differ as much as 0.3474 for the first regime (very stimulating) to 0.218 for the fifth regime (very limiting). The adjustment speeds for the set of estimates that include the sales condition information are somewhat lower and range between 0.268 for the first regime and 0.1874 for the fifth. This may be a result of the estimated target taking up more variation. Augmenting the target equation leads to more precise estimates of the adjustment coefficients in Table 6 and the other tables. In all estimates, the difference between the first and the third regime (finance neutral) are especially marked.

For each regime, measured adjustment speed is consistently higher for small firms, comparing adjustment speeds derived for the same specification of the target equation. In the third regime (finance neutral), adjustment speed is 0.2407 for small firms, 0.1777 for large firms and an intermediate 0.228 in the estimation that encompasses all firms. For the estimation using the sales indicator information in the target, the measured speeds are 0.2391 for small firms, 0.1666 for large firms and 0.1827 for the entire sample. Equally important, we can see that financing conditions matter more for small firms. For them, the speeds of adjustment varies more between the extremes (0.3565 and 0.3469 if finance is very stimulating vs. 0.2644 and 0.2352 if finance is very limiting) than this is the case for larger firms (0.2074 and 0.1900 if finance is very stimulating vs. 0.149 and 0.143 if finance is very limiting).

With five regimes, it is difficult to test for differences between individual regimes. In Table 7, I present results for the condensed regime partition R(2), where on each side the two extreme categories are aggregated. The general picture is similar. Again, the speed of adjustment is decreasing with financing conditions. However, there is barely any difference visible between the second category (finance neutral) and the third (finance limiting or very limiting). This may be the result of the inversion for α_4 that was mentioned in the discussion of Table 6, as the categories four and five in R(1) are lumped together in R(2). Again, small firms show a clearly higher speed of adjustment in all regimes and for both basic specifications.

Testing coefficient restrictions shows that regime matters. The hypothesis $\alpha_1 = \alpha_2$ is rejected on a 5% level for both of the estimations that use all firms. For the subsets of small and large firms, the respective coefficient estimates do not differ significantly. For small firms, this may be due to the lower number of observations. In the case of large firms, the measured adjustment speeds do not differ much indeed.

In Table 8, the exercise is repeated using R(3) as regime partition. This regime partition closely corresponds to the underlying theoretic ideas and also takes a possible bias in the measurement of adjustment speeds for rapidly downsizing firms into account. I concentrate on the comparison of the adjustment speed $1-\alpha_1$ for unrestricted stationary or expanding episodes with the adjustment speed $1-\alpha_2$ for financially constrained stationary or expanding episodes. For estimates using the entire sample, the differences in adjustment speed are significant on a 10% level for both specifications of the target equation. Without additional variables in the target, it is 0.2599 for stationary or expanding unconstrained firms and 0.2047 for their constrained counterparts. Augmenting the target equation by sales indicators leads to an adjustment speed of 0.2068 for stationary or expanding unconstrained firms and 0.1665 for their constrained counterparts. Repeating the differential analysis separately for small and for large firms shows that financing constraints do matter for small firms. Here, the adjustment speed is 0.3066 for unconstrained firms vs. 0.2331 for constrained firms using the target equation without sales indicators and 0.2433 vs. 0.1658 with the augmented target equation. This latter result is strongly significant, with a p-value of 0.0140. For large firms, the measured differences are neither statistically nor economically significant: the adjustment speeds cluster around 0.18 for both specifications.

As a result from these estimations and tests, we see that financing constraints slow down the speed of adjustment of firms. Furthermore, this effect is concentrated or perhaps even limited to smaller firms. With large firms, no clear speed differential can be detected. Ultimately we see that the speed of adjustment of small firms is clearly higher than for large firms. These results fit extremely well to what was obtained in Chapter 2 for capacity adjustment of UK firms, using an entirely different methodology on a different type of data.

6 Aggregate implications of adjustment heterogeneity

If the speed of adjustment is regime dependent, then the aggregate reaction to an overall shock depends on the composition, and changes in this composition are equivalent to changes in aggregate sensitivity. This is well known, but our method of relating the dynamic behaviour of individuals to survey information makes it particularly easy to trace the aggregate sensitivity and give up-to-date estimates about the current stance.

Figure 1 is based on the preferred regime partition R(3), with the results that were obtained using the entire sample. For demonstration purposes, I use the simple target equation specification, Table 8, Column (1), as it yields higher differences between regimes. The qualitative picture that results from using the results from the augmented target equation is very similar. The upper two panels of Figure 1 display the changing composition of the estimation panel with respect to adjustment regimes. The left panel refers to the unweighted averages, the right panel to the average weighted with the log of the real capital stock. It can easily be seen that the variation in composition is considerable and closely follows the business cycle in Germany.

The lower two panels show the aggregate sensitivity to a hypothetical aggregate shock that consists in an equiproportionate increase in the target level of all firms. Again both the unweighted and the weighted averages are given. The same type of approach would be possible for other, more complex adjustment equations, and various dynamic multipliers, eg first period, second, third etc. period effects. In the current setting, with one regime specific dynamic parameter, we simply need to multiply the shares with the associated adjustment coefficient to get the one-period sensitivity of labour or capital demand with respect to an aggregate shock in the target in the last period. The time variation in aggregate sensitivity is considerable, though not overwhelming: Aggregate sensitivity of capital demand is 0.247 in 1990, decreases to 0.215 in 1994 and returns to 0.250 in the last vintage of the micro data set, the year 1998.

The figure exemplifies how survey data on financing constraints or other regimes can be used for policy analysis. The aggregate sensitivity condenses the informational content of the microeconomic composition. With estimates of regime specific dynamics at hand, what drives the aggregate sensitivity is the changing composition of the aggregate. This composition is timely available in the course of the publication routines of survey agencies. When it comes to evaluating the survey data, the difficult process of estimating regime specific adjustment dynamics does not have to be repeated, as it is possible to rely on the coefficients estimated earlier.

Figure 1: Time varying sensitivity of capital demand to sales shocks

(for Regime Partition R(3), Table 8, Column I)

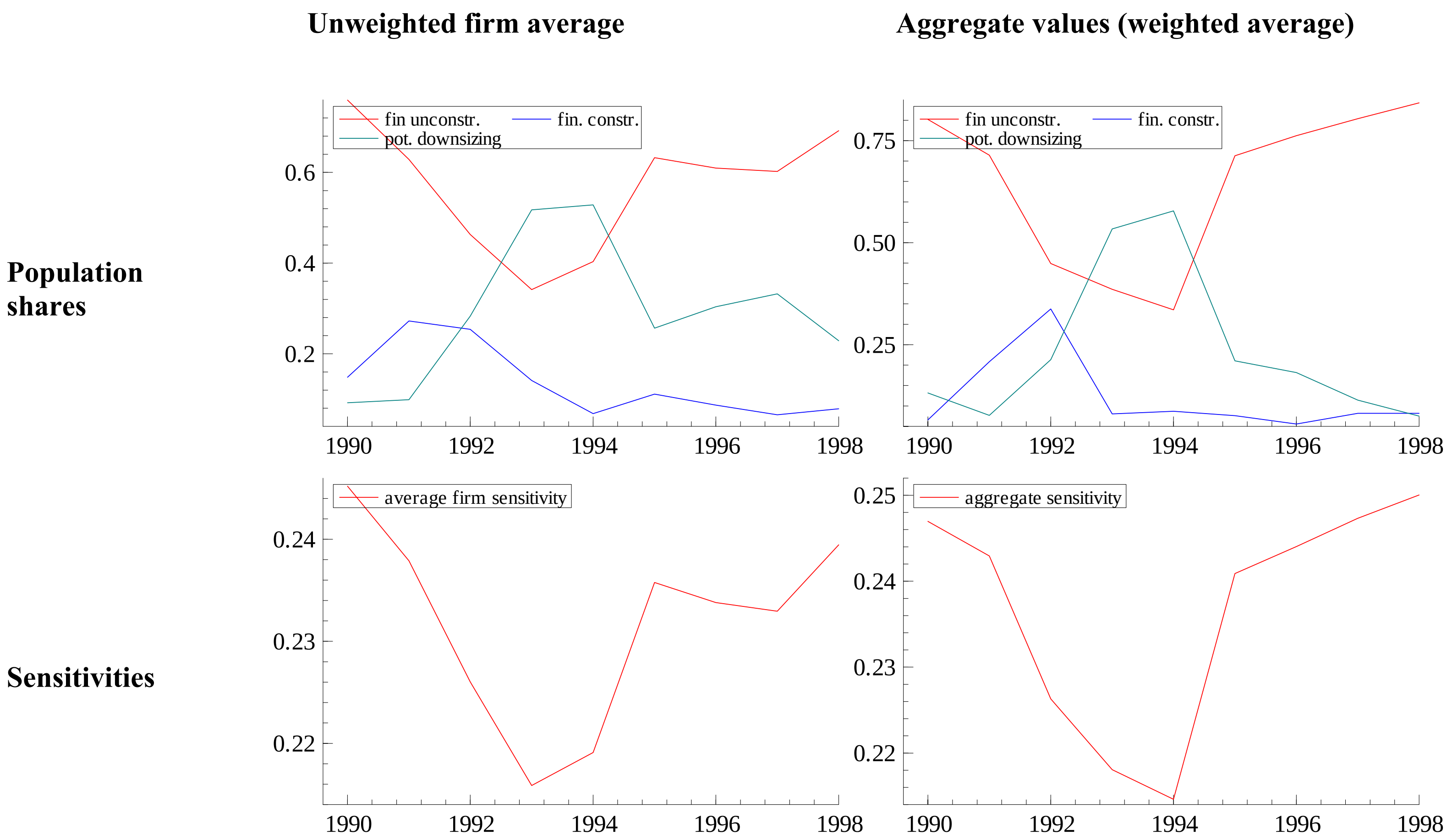

Table 1: Descriptive statistics for continuous variables

	# Obs.	Mean	Median	Standard deviation			Min.	Max.
Variable				*Overall*	*Between*	*Within*		
$\log K_{i,t}$	19,268	10.0338	9.9533	1.8429	1.7724	0.1363	4.4349	17.0356
$\Delta \log K_{i,t}$	16,097	0.0120	-0.0082	0.0925	0.0676	0.07105	-0.1378	0.5138
$\log S_{i,t}$	19,268	10.9051	10.8441	1.9289	1.8611	0.1810	4.6739	18.3246
$\Delta \log S_{i,t}$	16,097	0.03701	0.0421	0.1491	0.0824	0.1320	-0.6412	0.6730

Notes: All values are in natural logarithms of multiples of 1.000 Deutsche Mark, 1991 prices. Values for net real capital stocks are generated using the eternal inventory method on the basis of panel information on fixed investment and real depreciation rates. Starting values are computed on the basis of reported number of employees and time specific sector capital-labour intensities computed from German national accounts data.

Table 2: Breakdown by firm size classes

Size classes	# Firms	$\log K_{i,t}$	$\Delta \log K_{i,t}$	$\log S_{i,t}$	$\Delta \log S_{i,t}$
1-49 empl	619	7.5682	-0.0046	8.3284	0.0302
50-199 empl.	970	9.0500	0.0102	9.9118	0.0455
200 – 999 empl.	1,015	10.5367	0.0167	11.4293	0.0366
1000 and more empl.	567	12.4916	0.0199	13.4311	0.0313
All firms	3,171	10.0338	0.0120	10.9051	0.03701

Notes: See Table 1. Size classes are defined on the basis of employment information at the *start* of a consecutive string of firm observations.

Table 3: Financing and sales conditions for realised investment: Tabulations and panel variation

	Financing conditions			Sales conditions		
	Overall (%)	Between (%)	Within (%)	Overall (%)	Between (%)	Within (%)
Very stimulating	3.56	12.14	25.45	18.88	48.84	33.16
Stimulating	14.57	38.84	32.06	34.93	74.01	42.86
Neutral	58.32	82.17	66.94	16.03	43.30	32.03
Limiting	16.22	41.24	32.51	17.03	48.51	28.75
Very limiting	7.32	21.89	28.40	13.14	36.99	28.37
# Obs.	14,926			15,675		

Notes: Tabulations are for factors relating to investment carried out in the current year, given in percentage terms. See the text for the exact wording of the survey question. *Overall* percentages summarise results in terms of firm-years. *Between* columns repeats the breakdown in terms of firms, giving the percentage of firms that ever reported a specified value. *Within* columns give the fraction of time firms report a certain value, conditional on that value being reported at least once. A time invariant categorical variable would have a tabulation with each entry equal to 100% in the *within* column

Table 4: Transition matrix for regime partition R(2)

	Stimulating or very stimulating	Neutral	Limiting or very limiting	Total
Stimulating or very stimulating	1,092 (54.09%)	597 (29.57%)	330 (16.34%)	2,019 (100.0%)
Neutral	627 (9.14%)	5,418 (78.99%)	814 (11.87%)	6,859 (100.0%)
Limiting or very limiting	355 (12.54%)	744 (26.28%)	1,732 (61.18%)	2,831 (100.0%)
Total	2,074 (17.71%)	6,759 (57.72%)	2,876 (24.56%)	11,709 (100.0%)

Notes: Tabulations are for factors relating to investment carried out (or planned) for the current year, given in percentage terms. See the text for the exact wording of the survey question. The outcomes of financial factors for realised investment are condensed to three values by aggregating "very stimulating" and "stimulating" to one category and "very limiting" and "limiting" to another.

Table 5: Transition matrix for regime partition R(3)

	Finance not limiting and stationary or expanding	Finance limiting, and stationary or expanding	Potentially downsizing	Total
Finance not limiting and stationary or expanding	3,462 (71.96%)	448 (9.31%)	901 (18.73%)	4,811 (100.0%)
Finance limiting, and stationary or expanding	364 (29.76%)	503 (41.13%)	356 (11.87%)	1,223 (100.0%)
Potentially downsizing	905 (12.54%)	199 (26.28%)	1,437 (61.18%)	2,541 (100.0%)
Total	4,731 (55.17%)	1,150 (13.41%)	2,694 (31.42%)	8,575 (100.0%)

Notes: Regime partition *R(3)* is generated using responses on expected factors for next period's investment, lagged once, see the description in the main text. The first category combines the levels "very stimulating,", "stimulating" and "neutral" of the financing conditions indicator with the levels "very stimulating", "stimulating" and "neutral" of the sales conditions indicator. The second category combines the same levels of the sales indicator with the levels "limiting" or "very limiting" of the financing conditions indicator. The third category collects all observations where sales conditions were described as "limiting" or "very limiting".

Table 6: Adjustment speed according to financing conditions
Regime partition R(1), 5 regimes, based on factors for realised investment

Dependent variable: $\Delta \log K_{i,t}$	**(1) All firms** w/o sales cond. ind. in target	**(2) All firms** with sales cond. ind. in target	**(3) SMEs** w/o sales cond. ind. in target	**(4) SMEs** with sales cond. ind. in target.	**(5) Large** w/o sales cond. ind. in target	**(6) Large** with sales cond. ind. in target
Regime specific adjustment coeff.						
α_1 (fin. very stimulating)	0.6526 (0.0788)	0.7319 (0.0593)	0.6435 (0.1043)	0.6531 (0.0832)	0.7926 (0.0540)	0.8100 (0.0482)
α_2 (finance stimulating)	0.7194 (0.0343)	0.7798 (0.0308)	0.6898 (0.0547)	0.7149 (0.0451)	0.8106 (0.0332)	0.8187 (0.0296)
α_3 (finance neutral)	0.7720 (0.0286)	0.8173 (0.0231)	0.7593 (0.0381)	0.7609 (0.0374)	0.8223 (0.0294)	0.8334 (0.0229)
α_4 (finance limiting)	0.7540 (0.0351)	0.7998 (0.0295)	0.7246 (0.0462)	0.7500 (0.0516)	0.8233 (0.0328)	0.8385 (0.0263)
α_5 (fin. very limiting)	0.7802 (0.0349)	0.8126 (0.0311)	0.7356 (0.0578)	0.7648 (0.0587)	0.8510 (0.0348)	0.8507 (0.0309)
Additional vars. in target equation:						
Time dummies	yes	yes	yes	yes	yes	yes
Sales conditions indicator dummies	no	yes	no	yes	no	yes
Observations and specification tests						
Sargan-Hansen test	$\chi^2(203)=239.5$ $p=0.040$	$\chi^2(319)=331.6$ $p=0.302$	$\chi^2(203)=216.2$ $p=0.250$	$\chi^2(319)=321.4$ $p=0.452$	$\chi^2(203)=218.6$ $p=0.215$	$\chi^2(319)=307.8$ $p=0.663$
LM (1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
LM (2) test, p-value	0.000	0.000	0.029	0.033	0.000	0.000
LM (3) test, p-value	0.355	0.531	0.944	0.979	0.054	0.055
# Firms	2,753	2,744	1,299	1,292	1,454	1,452
# Obs.	10,723	10,675	4,426	4,398	6,297	6,277

Notes: Estimates for regime specific adjustment of the real capital stock as given in equation (xx). Estimation method: GMM on the basis of Quasi-Difference transformation QD2 as described in Chapter 3 and this text. For each estimate, the target equation for the capital stock contains $\log K_{i,t-1} - \log S_{i,t}$, time dummies and a firm fixed effect, modelling a reversion of capital intensity to a firm specific value conditioned by time effects to capture macroeconomic effects and technical progress. In estimates (2), (4) and (6), the target equation also contains category dummies for the sales conditions factor. Regime partition is based on the financing conditions indicator relating to investment carried out in the current year as stated by respondents, with each regime corresponding to one value the indicator may take, cf. Table 3. See the main text for the exact wording of the survey question. Instruments: lags 1-6 of regime dummies, lags 3-6 of $\log S_{i,t}$ and $\log K_{i,t}$ and time dummies, in estimates (2), (4) and (6) additionally lags 2-6 of sales conditions dummies. The Sargan-Hansen statistic is a test of overidentifying restrictions proposed by Sargan (1958) and Hansen (1982). The LM(*k*) tests are the p-values for the Lagrange Multiplier statistics for serial correlation of order *k* proposed by Arellano and Bond (1991). The robust standard errors from the second step estimation with a small sample correction based on Windmeijer (2005) are in parentheses. Estimation was executed using DPD package version 1.2 on Ox version 3.30 and extensive user written Ox routines.

Table 7: Adjustment speed according to financing conditions
Regime partition R(2), 3 regimes, based on factors for realised investment

	(1) **All firms** w/o sales cond. ind. in target	**(2)** **All firms** with sales cond. ind. in target	**(3)** **SMEs** w/o sales cond. ind. in target	**(4)** **SMEs** with sales cond. ind. in target	**(5)** **Large** w/o sales cond. ind. in target.	**(6)** **Large** with sales cond. ind. in target.
Regime specific adjustment coeff.						
α_1 (finance stimulating or very stimulating)	0.6899 (0.0338)	0.7591 (0.0335)	0.6514 (0.0594)	0.7284 (0.0503)	0.8204 (0.0331)	0.8280 (0.0277)
α_2 (finance neutral)	0.7533 (0.0281)	0.8108 (0.0230)	0.7178 (0.0463)	0.7765 (0.0373)	0.8529 (0.0279)	0.8514 (0.0204)
α_3 (finance limiting or very limiting)	0.7570 (0.0335)	0.8146 (0.0271)	0.7093 (0.0530)	0.7927 (0.0417)	0.8512 (0.0326)	0.8482 (0.0260)
Additional vars. in target equation:						
Time dummies	yes	yes	yes	yes	yes	yes
Sales conditions indicator dummies	**no**	**yes**	**no**	**yes**	**no**	**yes**
Testing coefficient restrictions:						
$\alpha_1 = \alpha_2$	$\chi^2(1) = 4.6649$ $p = 0.0308$	$\chi^2(1) = 5.4247$ $p = 0.0199$	$\chi^2(1) = 1.2357$ $p = 0.2663$	$\chi^2(1) = 1.5778$ $p = 0.2091$	$\chi^2(1) = 3.969$ $p = 0.0463$	$\chi^2(1) = 1.7816$ $p = 0.1820$
$\alpha_2 = \alpha_3$	$\chi^2(1) = 0.0157$ $p = 0.9003$	$\chi^2(1) = 0.0324$ $p = 0.8572$	$\chi^2(1) = 0.0547$ $p = 0.8151$	$\chi^2(1) = 0.1780$ $p = 0.6731$	$\chi^2(1) = 0.0312$ $p = 0.8598$	$\chi^2(1) = 0.0404$ $p = 0.8407$
$\alpha_1 = \alpha_3$	$\chi^2(1) = 3.2667$ $p = 0.0707$	$\chi^2(1) = 3.8619$ $p = 0.0494$	$\chi^2(1) = 0.9651$ $p = 0.4044$	$\chi^2(1) = 1.9542$ $p = 0.1621$	$\chi^2(1) = 1.7241$ $p = 0.1892$	$\chi^2(1) = 0.8589$ $p = 0.3540$
$\alpha_1 = \alpha_2 = \alpha_3$	$\chi^2(2) = 5.0136$ $p = 0.0815$	$\chi^2(2) = 5.7291$ $p = 0.0570$	$\chi^2(2) = 1.3159$ $p = 0.5179$	$\chi^2(2) = 2.2225$ $p = 0.3291$	$\chi^2(2) = 4.006$ $p = 0.1349$	$\chi^2(2) = 1.7819$ $p = 0.4103$
Observations and specification tests						
Sargan-Hansen test	$\chi^2(127) = 139.1$ $p = 0.219$	$\chi^2(243) = 242.3$ $p = 0.500$	$\chi^2(127) = 125.5$ $p = 0.520$	$\chi^2(243) = 231.4$ $p = 0.693$	$\chi^2(127) = 144.5$ $p = 0.138$	$\chi^2(243) = 231.7$ $p = 0.688$
LM (1) test, p-val.	0.000	0.000	0.000	0.000	0.000	0.000
LM (2) test, p-val.	0.000	0.000	0.024	0.028	0.000	0.000
LM (3) test, p-val.	0.467	0.644	0.966	0.878	0.059	0.059
# Firms	2,753	2,744	1,299	1,292	1,454	1,452
# Obs.	10,723	10,675	4,426	4,398	6,297	6,277

Notes: See notes to Table 6. Regime R(2) is defined on the basis of a condensed financing conditions indicator for realised investment. The levels "very stimulating" and "stimulating" are aggregated to one category and "limiting" and "very limiting" to another. See the transition matrix in Table 4 for this regime variable. The tests on equality of adjustment coefficients are standard χ^2 tests.

Table 8: Adjustment speed according to financing conditions and expansion mode Regime partition R(3), 3 regimes, based on lagged factors for expected investment

	(1) **All firms** w/o sales cond. ind. in target	(2) **All firms** with sales cond. ind. in target	(3) **SMEs** w/o sales cond. ind. in target.	(4) **SMEs** with sales cond. ind. in target	(5) **Large** w/o sales cond. ind. in target	(6) **Large** with sales cond. ind. in target
Regime specific adjustment coeff.						
α_1 (stat. or expanding, fin. unconstrained)	0.7401 (0.0404)	0.7932 (0.0280)	0.6934 (0.0536)	0.7567 (0.0368)	0.8200 (0.0328)	0.8143 (0.0271)
α_2 (stat. or expanding, fin. constrained)	0.7953 (0.0450)	0.8335 (0.0315)	0.7669 (0.0712)	0.8342 (0.0402)	0.8314 (0.0338)	0.8352 (0.0296)
α_3 (pot. downsizing)	0.8101 (0.0378)	0.8335 (0.0276)	0.7547 (0.0583)	0.8133 (0.0333)	0.8591 (0.0254)	0.8560 (0.0229)
Additional vars. in target equation:						
Time dummies	yes	yes	yes	yes	yes	yes
Sales conditions indicator dummies	**no**	**yes**	**no**	**yes**	**no**	**yes**
Testing coefficient restrictions:						
$\alpha_1 = \alpha_2$	$\chi^2(1) = 2.9646$ $p = 0.0851$	$\chi^2(1) = 3.244$ $p = 0.0717$	$\chi^2(1) = 1.3150$ $p = 0.2515$	$\chi^2(1) = 6.0392$ $p = 0.0140$	$\chi^2(1) = 0.5450$ $p = 0.4604$	$\chi^2(1) = 0.9980$ $p = 0.3178$
$\alpha_2 = \alpha_3$	$\chi^2(1) = 0.1653$ $p = 0.6843$	$\chi^2(1) = 0.00001$ $p = 0.9972$	$\chi^2(1) = 0.0373$ $p = 0.8468$	$\chi^2(1) = 0.4018$ $p = 0.5261$	$\chi^2(1) = 0.2220$ $p = 0.6375$	$\chi^2(1) = 0.7362$ $p = 0.3909$
$\alpha_1 = \alpha_3$	$\chi^2(1) = 4.2351$ $p = 0.0396$	$\chi^2(1) = 3.3049$ $p = 0.0691$	$\chi^2(1) = 1.4424$ $p = 0.2297$	$\chi^2(1) = 3.702$ $p = 0.0543$	$\chi^2(1) = 1.1121$ $p = 0.2916$	$\chi^2(1) = 3.6924$ $p = 0.0547$
$\alpha_1 = \alpha_2 = \alpha_3$	$\chi^2(2) = 5.2224$ $p = 0.0734$	$\chi^2(2) = 4.543$ $p = 0.1032$	$\chi^2(2) = 1.9475$ $p = 0.3777$	$\chi^2(2) = 7.0309$ $p = 0.0297$	$\chi^2(2) = 1.274$ $p = 0.5289$	$\chi^2(2) = 3.8085$ $p = 0.1489$
Observations and specification tests						
Sargan-Hansen test	$\chi^2(101) = 115.7$ $p = 0.151$	$\chi^2(217) = 210.9$ $p = 0.605$	$\chi^2(101) = 103.2$ $p = 0.420$	$\chi^2(217) = 200.1$ $p = 0.789$	$\chi^2(101) = 99.31$ $p = 0.529$	$\chi^2(217) = 214.9$ $p = 0.527$
LM (1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
LM (2) test, p-value	0.011	0.000	0.655	0.867	0.000	0.000
LM (3) test, p-value	0.343	0.259	0.439	0.299	0.413	0.356
# firms	2,334	2,334	1,047	1,047	1,260	1,260
# obs.	8,575	8,575	3,448	3,448	5,127	5,127

Notes: See notes to Table 6. Regime partition R(3) is computed using lagged responses on expected factors for the subsequent period's investment. The regime related to α_1 combines the levels "very stimulating,", "stimulating" and "neutral" of the financing conditions indicator with the levels "very stimulating", "stimulating" and "neutral" of the sales conditions indicator. The regime related to α_2 combines the same levels of the sales indicator with the levels "limiting" or "very limiting" of the financing conditions variable. The third regime, related to α_3, collects all observations where sales conditions were described as "limiting" or "very limiting". See the transition matrix in Table 5 for this regime partition. The tests on equality of adjustment coefficients are standard χ^2 tests.