Bellgardt, Egon; Behr, Andreas

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Dynamic Q-investment functions for Germany using panel balance sheet data and a new algorithm for the capital stock at replacement values

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Dynamic Q-investment functions for Germany using panel balance sheet data and a new algorithm for the capital stock at replacement values

Andreas Behr
(University of Frankfurt)

Egon Bellgardt
(University of Frankfurt)

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Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 95 66-1
Telex within Germany 4 1 227, telex from abroad 4 14 431, fax +49 69 5 60 10 71

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax No. +49 69 95 66-30 77

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Abstract

The paper explores the investment behaviour of German firms in the context of the *Q*-approach, which plays a dominant role in empirical investment research. The analysis is based on the Deutsche Bundesbank's corporate balance sheet statistics. The panel data set contains some 2,300 German firms' balance sheet data covering the years 1988-1998.

While the *Q*-theory is mainly applied on the basis of stock market data, which facilitates the exploitation of market expectations and the calculation of average *Q*, the direct forecasting approach (Chirinko 1993) suggested by Abel and Blanchard (1986) and extended to panel data by Gilchrist and Himmelberg (1995, 1998) enables the *Q*-theory to be applied to non-quoted firms which are by far the majority in Germany.

One of the key variables when using balance sheet data, which has attracted much detailed research, is firms' net capital stock at replacement costs. The challenge is to transform historical cost data, depreciated at non-economic, tax-oriented depreciation rates, into unreported and probably unknown economically meaningful data at actual replacement values. We suggest a complex procedure for calculating reliable replacement values of a firm's capital stock.

To calculate *Q* we follow two different operationalisation strategies. First we estimate average *Q* based on balance sheet data by forecasting the present value of future profits using a VAR model. Second, we estimate marginal *Q* following the approach suggested by Gilchrist and Himmelberg. We compare the results from two different estimation techniques for dynamic investment models, GMM and direct bias correction.

The results show that marginal as well as average *Q* influence investment significantly. When classifying the firms by size, we find that smaller firms react more strongly to *Q* and, to a lesser extent, to lagged investment.

JEL-code: C33, C81, G31,D24

Keywords: investment, *Q*, capital stock, replacement costs, VAR, dynamic panel data

Zusammenfassung

Die vorliegende Arbeit untersucht das Investitionsverhalten deutscher Unternehmen im Rahmen der *Q*-Theorie, die eine der dominierenden Investitionstheorien darstellt. Grundlage der geschätzten Investitionsfunktionen ist die Unternehmensbilanzstatistik der Deutschen Bundesbank. Der Paneldatensatz umfasst über 2300 Unternehmen und den Zeitraum 1988 bis 1998.

Die übliche Verwendung von Aktienkursen zur Berechnung des durchschnittlichen *Q* beschränkt die Anwendung der *Q*-Theorie auf börsennotierten Unternehmen. Die explizite Modellierung eines Prognosemodells (direct forecasting appraoch, Chirinko (1993)) in Anlehnung an Arbeiten von Abel and Blanchard (1986) und Gilchrist and Himmelberg (1995, 1998) ermöglicht die Anwendung auch für nicht börsennotierte Unternehmen, die in Deutschland eindeutig dominieren.

Eine zentrale Größe der Analyse des Investitionsverhaltens auf der Grundlage von Unternehmensbilanzdaten ist der Kapitalstock der Unternehmen zu Wiederbeschaffungskosten anstelle des bilanziellen Nettoanlagevermögens zu historischen Anschaffungskosten. In der Arbeit wird ein komplexer Algorithmus zu einer möglichst exakten Schätzung vorgeschlagen.

Zur Berechnung von *Q* werden zwei unterschiedliche Operationalisierungsstrategien verfolgt. Zum einen wird in Anlehnung an Abel und Blanchard das durchschnittliche *Q* über eine Schätzung des Marktwertes des Eigenkapitals mittels eines Vektor-Autoregressiven-Modells für Paneldaten ermittelt. Zum anderen wird auf dem Ansatz von Gilchrist and Himmelberg beruhend eine Abschätzung des marginalen *Q* vorgenommen. Die Ergebnisse der *Q*-Investitionsfunktionen werden für zwei alternative Schätztechniken, GMM und eine direkte Biaskorrektur, verglichen.

Es zeigt sich, dass sowohl das durchschnittliche als auch das marginale *Q* die Investitionen in signifikantem Ausmaß beeinflussen. Die Analyse für Größenklassen zeigt, dass im wesentlichen kleinere Unternehmen in stärkerem Maße auf *Q* und in geringerem Maße auf zeitlich verzögerte Investitionen reagieren.

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1. Introduction

The determinants of firms' investment spending have been the focus of academic research for several decades. Improving the foundations of investment theory as well as the policy implications is a most interesting objective. Investment spending is known to be very volatile and therefore one of the driving forces of macroeconomic activity.

In empirical research on investment several approaches have been used (see for an overview Chirinko 1993). One important approach are so called *Q* models (Tobin 1969).[1] *Q* models of investment are attractive in several respects. Theoretically the *Q*-model can be derived explicitly from an optimization problem which the firm faces when deciding about new investments.[2] Under quite strong assumptions, a linear relationship can be derived between the ratio of investment to the capital stock and a measure of *Q*. Theoretically *Q* is a sufficient statistic for determining the investment decision if the capital market is perfect.[3]

When using balance sheet data for an empirical analysis of firms' investment decisions researchers face the problem of non-adequate concepts for several variables. The measurement concepts underlying the balance sheet data often do not match the economic meaning that interests the researcher. One of the key variables which has attracted much detailed research is firms' net capital stock at replacement costs. The challenge is to transform historical cost data depreciated at non-economic, tax-oriented depreciation rates into unreported and probably unknown economically meaningful data at actual replacement values. First of all, therefore, we use a complex procedure for calculating reliable replacement values of a firm's capital stock.[4]

The second problem is that no stock prices are available for non-quoted firms, which makes it impossible to follow the usual approach when applying the *Q*-theory of using stock market data to calculate the market value of equity. The problem is circumvented by using a vector-autoregressive approach (VAR) for panel data to estimate the present values of the future returns on capital in order to calculate *Q*. This direct forecasting approach, as Chirinko (1993) named it, is based on a VAR forecasting model and was first suggested by Abel and Blanchard (1986) for aggregate times series. This approach was extended in the context of the *Q*-theory by Gilchrist and Himmelberg (1995, 1998) to panel

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* We would like to thank Heinz Herrmann for his support and helpful comments.

1 In the following we use the upper case symbol *Q* throughout the text indicating all different measures, whether they are based on share prices or on values gained by direct forecasting systems.

2 Von Kalckreuth (2001) analysed investment behaviour in Germany on the basis of an implicit (user cost) model with the same dataset used in this paper.

3 But see Caballero/Leahy (1996) for the case of fixed costs of capital stock adjustment.

4 See Hayashi (1997) for a discussion of the biases resulting from the use on non-adequate measures of the capital stock.

data. The advantage of this direct forecasting approach is that it enables the Q-theory to be applied to non-quoted firms as well.

In our study we follow two different operationalisation strategies. First we estimate an average Q comparable to Tobin's Q by forecasting future profits using a VAR-model along the lines of Abel and Blanchard. Second, we estimate marginal Q following the approach suggested by Gilchrist and Himmelberg, which is based on a restrictive formulation of the underlying production process.

The results show a very strong influence of the calculated average as well as marginal Q on investment for a large panel of German firms. Therefore, we find that the Q-theory is well suited for application to non-quoted firms on the basis of balance sheet data using a direct forecasting approach.

2. Theoretical considerations

The economic models of business fixed investment can broadly be classified into two classes of models.[5] The distinguishing feature is whether or not the models explicitly take account of the process of adjustment of the capital stock. In both classes of models the optimal level of the firms capital stock results as the solution of the profit maximization problem. But where the class of older models (Jorgensen (1963, 1971)) does not explain the optimal path of adjustment of the actual capital stock to the optimal one, the second class of models explicitly derives the optimal evolution of the capital stock from the underlying optimization problem. The difference therefore can be seen in the step from the static problem of optimal factor demand to dynamic investment models. This step can be performed either by ad hoc specifications or by an explicit derivation of the adjustment path undertaken in the investment models based on the Q-theory .

Naturally, this advantage is achieved by making strong assumption about the costs of adjusting the capital stock, which leads to a rationalization of the observed slow adjustment. In most cases the costs of adjustment are assumed to be strictly convex in the amount of investment what implies increasing marginal costs. Therefore deviations between the actual and the optimal capital stock will be reduced through a sequence of smaller investments rather than through a one-time large change in the capital stock. The costs of adjustment can be thought of as installation costs or costs caused by the disruptions of the production process when new investment is undertaken.

In the following the Q-model including an explicit formulation of the adjustment costs is illustrated. In the basic Q-model the firm faces the following maximization problem:

$$V_t = E\left[\sum_{j=0}^{\infty} \beta_{t+j} \Pi_{t+j} \mid \Omega_t\right]$$

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5 See Blundell/Bond/Meghir (1995).

The firm is assumed to maximize the expected value of the sum of discounted profits Π_t given the state of information Ω at time t.

The discount factor between period t and period $t + j$ is denoted by β_{t+j} and is assumed to be the product of the single-period discount rates:

$$\beta_{t+j} = \prod_{i=1}^{j} (1 + r_{t+i})^{-1} \text{ , } j = 1, 2, 3, ..., \infty.$$

The profit Π_t is the difference between sales and costs of production taking into account the adjustment costs and the cost of investment:

$$\Pi_t = p_t [F(K_t, L_t) - G(I_t, K_t)] - w_t L_t - p_t^I I_t$$

The output is given by the amount of production F minus the lost output G caused by adjusting the capital stock. The firm is assumed to be producing on the basis of the given capital stock K_t while other factors of production L_t, mainly labour, are assumed to be adjusted instantaneously. The function of adjustment cost G is assumed to be strictly convex in investment and to be additively separable from the gross production function.

If asset markets are efficient in the sense that assets are valued at the expected present value of the associated income streams, then the value of the firm's capital stock V_t is the stock market value of the firm when abstracting from other assets beside the capital stock. The maximization problem the firm faces can therefore be expressed as a dynamic programming problem.

Using the first-order derivatives of the maximization problem it can be shown that, in equilibrium, the ratio of the shadow value to the replacement cost (which includes the adjustment costs) of an additional unit of capital should be one.

Assuming that markets are competitive, the firm is a price taker in all markets, and the ratio of the shadow value of capital in period t to the price of a unit of investment is known as marginal Q.

To derive a linear relation between marginal Q and investment, some rather restrictive assumptions have to be made concerning the adjustment cost function. If a quadratic adjustment cost function is assumed for mathematical convenience (Summers 1981), it can be shown that marginal adjustment costs increase linearly with the rate of investment and that the rate of investment is a linear function of marginal Q.

So far only marginal Q has been analysed. Following Hayashi (1982) it is also possible to derive a linear relation between ***average*** Q and investment. To derive a simple relation between marginal Q and average Q it is necessary to assume, besides perfect capital and product markets, that the production function $F(K_t, L_t)$ and the adjustment cost function

$G(I_t, K_t)$ are homogeneous of degree one in their arguments. In other words, it is assumed that the production function has constant returns to scale.

3. The data source

The empirical analysis is based on the Deutsche Bundesbank' corporate balance sheet statistics.[6] This data base covers about 50,000 to 70,000 enterprises each year, which represent about 4% of the total number of enterprises in Germany. In the context of its rediscount lending operations the Bundesbank collects the financial statements of firms using trade bills to assess the creditworthiness of bill-presenting firm.[7]

Because the sample is biased towards larger enterprises, it covers about 75% of the total turn-over of the corporate sector in western Germany. The period covered by our sample is from 1987 to 1998.

Starting with a very large data set the number of observations decreases considerably through incomplete balance sheets, outlier control and balancing. In particular, the need to use the detailed schedule of fixed asset movements (Anlagespiegel) in order to apply our algorithm for calculating the capital stock at replacement costs shrinks the available data to 2,303 firms included in the final estimations.[8]

The theoretical concept of the Q-theory of investment is microeconomic. Hence the use of firm-level data seems the natural way to apply an empirical test of the theory. But using individual balance sheet accounts has some caveats: the sample is not random and the data include noise from individual irregularities. Nevertheless, the theory seems to be better applicable to individual firm data. What leads to severe problems in using the balance sheet for economic analysis is the fact that the majority of the data (85%) is based on tax balance sheets. Therefore, the figures represented in the balance sheets accord with the legal descriptions as defined in tax law and differ from the theoretical concepts in several ways.[9] To overcome these problems as far as possible, great efforts are made in the measurement procedures; they are described in the following sections.

4. The capital stock at replacement costs: A new algorithm

The most prominent approaches for this transformation are the ones proposed by Lindenberg/Ross (1981), the NBER-approach (Hall et.al. (1988)) and the algorithm suggested by Lewellen/Badrinath (1997). In this paper we suggest an alternative algorithm which, according to our understanding and the results of a comparison based on Monte Carlo simulations, is almost comparable to the precise results of the algorithm by Lewellen and Badrinath but has considerable lower data requirements.

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6 For an overview of empirical work based on this data base see Stöss (2001).

7 See Deutsche Bundesbank (1998) and von Kalckreuth (2001), p. 9.

8 For details about the data source and cleaning procedures see the appendix.

9 See Deutsche Bundesbank (1998) and von Kalckreuth (2001).

In the following section we sketch the aforementioned approaches and try to show the core idea as well as the data requirements for the implementation, before we present our own approach. The next section contains a Monte Carlo simulation intended to compare the outcomes of the different approaches with our own suggested algorithm.

4.1. A short review of the literature

4.1.1. Lindenberg und Ross (1981)

The algorithm by Lindenberg and Ross starts from year $t = 1$ where the book value at historical costs less accumulated depreciation is taken as an approximation for the unknown net capital stock at replacement values. At the beginning of period $t = 1$ we have (in the following K^* denotes capital stock at replacement costs while K denotes the book value)

$$K_t^* = K_t \, .$$

In the following periods the capital stock is updated taking into account the depreciation rate (δ, book rate), price changes (i) and the technical process (θ) as well as gross investment (I_t):

$$K_t^* = K_{t-1}^* \frac{(1+i)(1-\delta)}{(1+\theta)} + I_t \, .$$

The capital stock contains fixed assets as well as inventories. The procedure described above is applied to fixed assets. With respect to inventories two cases are distinguished:

- When using FIFO (First-In-First-Out) the valuation of the stock is rather close to replacement costs and the book values remain unadjusted.
- When using LIFO (Last-In-First-Out) greater discrepancies will occur. In this case the book values of inventories will be adjusted using a procedure close to the one described above and the parameter settings $\delta = 0$ and $\theta = 0$.

4.1.2. "NBER-approach" by Hall et al (1988)

While inventories are treated with a technique similar to the approach of Lindenberg and Ross the NBER-approach adjusts the book value of fixed assets for price changes. Central to the algorithm is the assumption about the average age $\overline{a}$ of the existing capital stock. Thus if $\overline{a}$ =4, the adjustment of the book value takes into account the price changes of capital goods, π, for the last 4 years. In general the estimated capital stock in period t is given by

$$K_t^* = K_t \prod_{j=1}^{\overline{a}} (1+\pi_{t-j+1}) \, .$$

It is evident that the quality of the estimation hinges on the correctness of $\bar{a}$. The average age is calculated using historical balance sheet data for depreciation D:

(1) Calculation of average age in period t:

$$a_t = \frac{\sum_{\tau=1}^{t} D_\tau}{D_t} .$$

(2) The average lifetime n_t for capital goods in period t is given by:

$$n_t = \frac{K_t^g}{D_t} ,$$

where K_t^g denotes the gross capital stock (no depreciation subtracted) at historical costs in period t.

(3) The estimated lifetimes are smoothed over five periods:

$$n_t^* = \frac{1}{5} \sum_{j=0}^{4} n_{t-j} .$$

(4) The final estimate of the average age is given by adjusting the preliminary estimate a_t with the ratio of smoothed lifetime to lifetime calculated for period t:

$$\bar{a} = a_t \frac{n_t^*}{n_t} .$$

4.1.3. Lewellen and Badrinath (1997)

Compared to the two algorithms described above, the approach suggested by Lewellen and Badrinath is more complex. The basic idea is to disaggregate the actual capital stock into the years of purchase in the first step and the price adjustment for the different vintages in the second step. Like the $\bar{a}$ in the NBER-approach, this approach contains a magical number as well. This time the key number for the quality of the procedure's results is the longest lifetime of capital goods $\tilde{n}$. Assuming that number is correct, the actual capital stock contains investment goods of the last $\tilde{n}$ vintages I_t:

$$K_t^g = \sum_{\tau=t}^{t-(\tilde{n}-1)} I_\tau .$$

To estimate $\tilde{n}$ we start with $\tilde{n} = 1$ and increase $\tilde{n}$ until the following inequality holds:

$$\sum_{\tau=t}^{t-(\tilde{n}-1)} I_\tau \le K_t^g < \sum_{\tau=t}^{t-\tilde{n}} I_\tau .$$

If

$$\sum_{\tau=t}^{t-(\tilde{n}-1)} I_\tau < K_t^g ,$$

the difference between cumulative investment and the gross capital stock at historical costs

$$K_t^g - \sum_{\tau=t}^{t-(\tilde{n}-1)} I_\tau > 0$$

is added to the oldest still-living vintage of investment.

Now we are interested in the share $\tilde{g}_\tau$ of the vintage I_τ that is still contained (not fully depreciated) in period *t*. Given the period of purchase τ under the assumption of linear depreciation for $\tilde{n}$ periods, the still-living share of the vintage is given as

$$\tilde{g}_\tau = \frac{2\tilde{n} - 2(t-\tau) - 1}{2\tilde{n}}, \quad \tau = t - \tilde{n} + 1, ..., t .$$

Summing the parts, the replacement value of the net capital stock for period *t* (starting point) can be estimated as:

$$K_t^* = \sum_{\tau=t}^{t-(\tilde{n}-1)} I_\tau \tilde{g}_\tau \frac{P_t}{P_\tau} .$$

Adjustment routines

The algorithm leads to estimates of cumulative depreciations of the capital goods which are still contained in the capital stock. These estimates DK_t^* might differ from the book values of cumulative depreciations DK_t. This possible discrepancy will be eliminated via the following adjustment routine.

The estimates of cumulative depreciations of still-living capital goods are given by

$$DK_t^* = \sum_{\tau=t}^{t-(\tilde{n}-1)} I_\tau (1 - \tilde{g}_\tau) .$$

These estimates are contrasted with the book value of cumulative depreciations of still-living goods:

$$DK_t = K_t^g - K_t .$$

If we have

$$DK_t > DK_t^*,$$

the difference

$$DK_t - DK_t^*,$$

will be added to the oldest vintage still living .

If we have

$$DK_t < DK_t^*,$$

all estimated depreciations will be adjusted (diminished) by the following ratio:

$$\frac{DK_t}{DK_t^*}.$$

This adjustment routine guarantees the equality of estimated and balance sheet data for the net capital stock at historical costs.

4.1.4. Critique

The Lindenberg-Ross-approach is rather simple and easy to implement. But it is obvious that the quality of the estimated capital stock at actual prices will increase over time. The quality of the initial estimate will be rather poor owing to overly fast depreciation of book values because of tax considerations and the neglecting of capital goods price changes. The updating of the capital stock might also be biased because book depreciation rates probably overstate economic depreciation rates. Our own empirical estimates will show that initially the book value amounts on average to only 40% of the economically meaningful replacement value.[10]

As in the approach taken by Lindenberg and Ross, in the NBER-approach it is assumed that book depreciations equal economic depreciations. Especially for German accounting data, there will be major discrepancies because in general the tax-oriented depreciation rates will exceed the economic rates. The calculations of average age and average lifetime ignore the fact that the stock of fixed assets in a period t is a composition of several investment vintages.

The approach taken by Lewellen and Badrinath is by far the most complex of the three discussed. By taking into account the age structure of the still-living capital stock, the price

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[10] One solution often applied in empirical work is to leave out several years at the beginning of the period covered. While that avoids using the worst estimates at the beginning of the estimation period, there will still be a strongly decreasing measurement error over time.

adjustment can be expected to be rather precise. The main disadvantage of this approach can be seen in the rather high data requirements. To estimate the capital stock for period t the investment data for the $\tilde{n}$-1 years preceding year t have to be given. Taking into consideration the rather long lifetime of structures, this data requirements will hardly ever be met when working with micro balance sheet data. Finally, the assumption of an equal lifetime of all capital goods seems to be rather oversimplifying.

4.2. A new algorithm

4.2.1. The basic idea

The basic idea of the new algorithm which we propose is to split the actual capital stock into two additive components. The first component contains the vintages which are still alive and already belonged to the capital stock at the beginning of the first year in the data set. We will add the subscript "old" to indicate this component. (In our data set this was the year 1987.) The second component consists of the capital goods which were acquired during the years covered by the data set and still belong to the capital stock. This component will be indicated by the subscript "new". For these two components we apply different adjustment procedures to transform the book values at historical costs and tax-driven depreciations into economically meaningful net capital stock figures at replacement costs. The final estimate of the capital stock will therefore be

$$K_t^* = K_{old,t}^* + K_{new,t}^* .$$

Let us first consider the "new" component. For this component the investment at actual prices for period t is covered in the available data set. Each vintage leaves the capital stock according to the retirement function commonly employed in the classical perpetual-inventory procedure. In addition, each year the capital stock is revalued so as to take account of the price development of capital goods.

Now let us look at the "old" part of the capital stock. The crucial point is to disaggregate the existing capital stock at the beginning of the first year covered by the data set t_0 into its vintages. If this is achieved in a plausible way, each vintage leaves the capital stock in line with the retirement function in the same way as the vintages of the "new" capital stock.

Besides this disaggregation into the different vintages, a second disaggregation is the important separation into structures and equipment. These two components are characterized by very different life-times which are associated with very different depreciations as well as different price changes.

As the depreciations given in the balance sheet data are mainly driven by tax considerations, their use would lead to a severe underestimation of the life time of capital goods. Therefore we use sectoral data for depreciation rates and capital goods' lifetimes which we assume will be closer to economic reality. Since the data set does not contain any price information, we also use sectoral price data. Both sectoral data sets are disaggregated into structures and equipment. The inventories are not revalued. Given that most firms employ the First-In-First-Out valuation scheme, we take the book values as beeing sufficiently close to replacement values. In this case (FIFO) there will only be minor differences between book values and replacement values. In the next section of the paper we will formalize the algorithm and present further details.

4.2.2. The disaggregation of the first period's capital stock into different vintages

The detailed schedule of fixed asset movements (Anlagenspiegel) contains information concerning the sum of all past investment still in stock at historical costs (gross capital stock at historical costs, K_t^g).

Disaggregation into structures and equipment

In our starting period t_0 we disaggregate the value of the capital stock ($K_{t_0}^g$) into structures and equipment based on the respective shares of structures and equipment in the balance sheets:

$$K_{t_0}^{g,j} = K_{t_0}^g \cdot \frac{K_{t_0}^j}{K_{t_0}}, \quad j\text{=1,2 (structures, equipment)},$$

with:

$K_{t_0}^{g,j}$ accumulated still-living investment at historical costs, typ *j*

$K_{t_0}^g$ accumulated still-living investment at historical costs (Anlagenspiegel), aggregate

$K_{t_0}^j$ net capital stock at historical costs (balance sheet), typ *j*

K_{t_0} net capital stock at historical costs (balance sheet), aggregate

In the following all calculations are performed at the disaggregated level for structures and equipment separately. To improve readability we leave out the subscript *j*.

Sectoral adjustment in year t_0

We do not make the counterfactual assumption of equality between historical cost data and actual replacement values. This procedure would lead to a severe underestimation of the net capital stock at actual replacement values. Instead we use sectoral data supplied by the Federal Statistical Office (Statistisches Bundesamt) to adjust for the discrepancies stemming from the different depreciation methods and price schemes.

The starting point is the firm level balance sheet value adjusted for the sectoral ratio for year t_0:

$$K_{t_0}^{*} = K_{t_0}^{g} \cdot \frac{K_{t_0}^{r,s}}{K_{t_0}^{g,h,s}},$$

$K_{t_0}^{g,h,s}$ gross capital stock at historical costs in sector s,

$K_{t_0}^{r,s}$ net capital stock at replacement values in sector s

adjustment takes into account the different price scheme as well as the difference between gross and net capital stock. It is obvious that the adjusted values in the initial year t_0 will be the closer to the true value the more the structure of firm i's capital stock resembles the structure of the capital stock in sector s in terms of both goods and age.

4.2.3. The retirement of the investment vintages

We disaggregate a vintage t into parts of different lifetime n. α_n denotes the part of a vintage with lifetime n (it retires after being n years in stock) and N is the maximum lifetime. In the course of its maximum lifetime N the vintage will retire completely. Therefore we have

$$\sum_{n=1}^{N} \alpha_n = 1$$

and

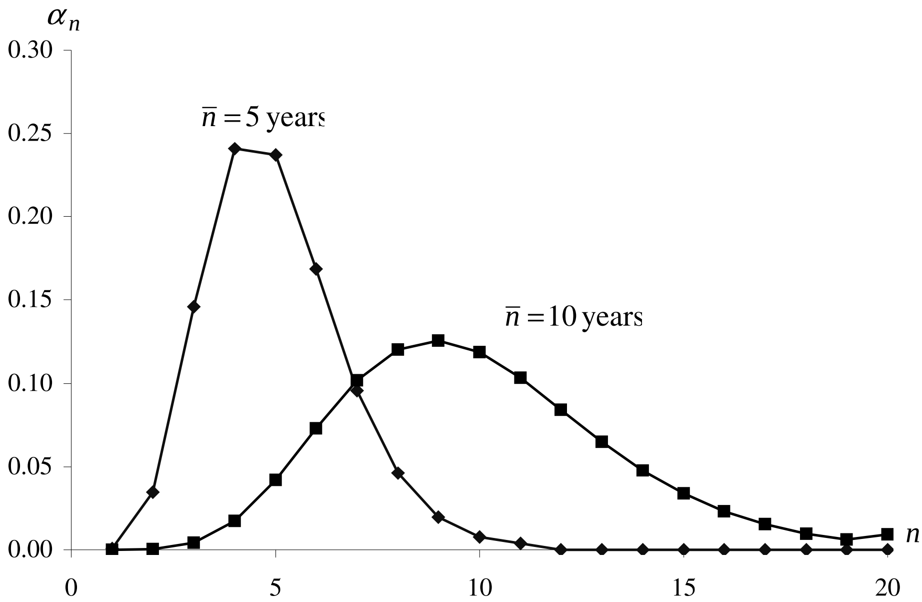
$$I_t = \sum_{n=1}^{N} I_t \alpha_n .$$

For determining the retirement ratios α_n we use the gamma function, which is also used by the Federal Statistical Office:

$$\alpha_n = \alpha(\bar{n}, n) = \frac{9^9}{\bar{n}^9 \cdot 8!} \cdot n^8 \cdot e^{\frac{-9 \cdot n}{\bar{n}}} .$$

This gamma function tells us which part of a fixed asset with average lifetime $\bar{n}$ retires at the age of n years.

Figure 1: The retirement function for average lifetimes of 5 and 10 years



For the individual firm i the average lifetime $\overline{n}$ of the sector the firm belongs to is used.[11] It is It is worth noting at this point that average lifetimes for structures and equipment differ considerably. These will be taken into account at the sectoral level.

In the next step we calculate linear depreciations of the vintage $\tau \geq t_0$ in period k:

$$D_{\tau,k} = I_\tau \cdot \sum_{n=1}^{N} \alpha_n \delta_{j,n} \ ,$$

with

n lifetime

N maximum lifetime

j age (=k-τ+1) of vintage τ in period k

$\delta_{j,n}$ depreciation rate, taking the half-year rule into account (hence we assume fixed assets join the firm in the middle of the year)

$$\delta_{j,n} = \begin{cases} \frac{0,5}{n} & \text{if } j = 1 \\ \frac{1}{n} & \text{if } 1 < j \leq n \\ \frac{0,5}{n} & \text{if } j = n+1 \\ 0 & \text{if } j > n+1 \end{cases}$$

Accumulating these depreciations from starting period t_0 until actual period t results in

11 Attempts to estimate the average lifetime for firm i individually would require very long time series, especially for structures, which usually will not be available in micro panel data sets.

$$DK_{\tau,t} = \sum_{k=\tau}^{t} D_{\tau,k} = \sum_{k=\tau}^{t} I_{\tau} \cdot \sum_{n=1}^{N} \alpha_n \delta_{j,n} \ , \quad j = k\text{-}\tau\text{+}1.$$

The price changes will be taken into consideration by using sectoral price indices P_t/P_τ where period t is the actual year and τ is the year the investment took place.

The replacement value of the capital stock less depreciation at the beginning of period t is the sum of the still-living investment adjusted for price changes:

$$K^{*}_{new,t} = \sum_{\tau=t_0}^{t} \left(I_\tau - DK_{\tau,t}\right)\frac{P_t}{P_\tau}.$$

4.2.4. Disaggregation of the capital stock at the beginning of the initial year into its vintages and retirements

The initial estimate of the capital stock is disaggregated into its vintages of investment separately for structures and equipment. To achieve this disaggregation several assumptions are necessary:

- the retirement function is stable over time,
- investment in the prior years has taken place evenly,
- the capital goods depreciate linearly over time.

These assumptions imply:

- what shares of investment vintages still belong to the capital stock, and
- the average lifetime of the vintages.

Let us denote the oldest vintage still belonging to the capital stock with τ_0. Then summing the depreciations and taking into account the price adjustment P_t / P_{t_0-1} we obtain the replacement value less depreciation of the capital goods still living in year t_0 at the end of year t:

$$K^{*}_{old,t} = \left(K^{*}_{old,t_0-1} - \sum_{\tau=t_0-N}^{t_0-1} DK^{old}_{\tau,t} \right) \frac{P_t}{P_{t_0-1}}.$$

The calculation of the depreciations

The counterpart to the retirement function is the survival function. This function tells us which part of the fixed asset is not retired yet at its age of n years:

$$g_n = \begin{cases} 1 & \text{if } n=1 \\ g_{n-1} - a_{n-1} & \text{if } n>1 \end{cases} .$$

Using the survival function, the age structure of the gross capital stock at the beginning of the initial year t_0 (or at the end of year $t_0 - 1$) can be derived.

Let

$$G = \sum_{n=1}^{N} g_n ,$$

then the share of the gross capital stock at the end of period t_0- 1 from investment taking place at year $\tau < t_0$ with age $j = t_0 - \tau$ is given by

$$\frac{g_j}{G} .$$

Hence the total value of investment vintage $\tau < t_0$ still alive in the period $t_0 - 1$ at replacement costs of the year $t_0 - 1$ can be estimated as

$$K^*_{t_0-1,\tau} = K^*_{t_0-1} \cdot \frac{g_{t_0-\tau}}{G} .$$

Since

$$\frac{g_j}{G} = \frac{\alpha_j + \alpha_{j+1} + \ldots + \alpha_N}{G}$$

this figure can be disaggregated into fractions with different lifetimes j:

$$K^*_{t_0-1,\tau} = \frac{K^*_{t_0-1}}{G} \cdot \sum_{j=t_0-\tau}^{N} \alpha_j .$$

The depreciations of vintage $\tau < t_0$ in period k are

$$D^{old}_{\tau,k} = \frac{K^*_{t_0-1}}{G} \cdot \sum_{n=1}^{N} \alpha_n \delta_{j,n} ,$$

$j = k - \tau + 1$ age of vintage τ in period k.

The cumulative depreciations of vintage $\tau < t_0$ from starting period t_0 until actual period t

are

$$DK_{\tau,t}^{old} = \sum_{k=\tau}^{t} D_{\tau,k}^{old} = \sum_{k=\tau}^{t} \frac{K_{t_0-1}^{*}}{G} \cdot \sum_{n=1}^{N} \alpha_n \delta_{j,n} \ , \quad j = k\text{-}\tau\text{+}1.$$

These estimated depreciations are valued at replacement costs of the year $t_0 - 1$. The final adjustment using the price relation P_t / P_{t_0-1} leads to the estimation at replacement costs of year *t*.

4.3. A comparison of the different approaches

In this section of the paper we run a Monte-Carlo simulation to assess the performance of the algorithms by Lindenberg/Ross, the NBER approach, the algorithm proposed by Lewellen/Badrinath and our own proposed alternative algorithm.

- The average lifetime $\bar{n}$ of fixed assets is 10 years, evenly distributed between 5 and 15 years.
- Each firm has a specific average lifetime $\bar{n}_i$ of its fixed assets and a specific retirement function.
- The retirement rates α_{in} of fixed assets with lifetimes *n* = 5, 6, ..., 15 for firm *i* are drawn at random. They will be held constant over the whole simulation period. The average lifetime of the firms fixed assets is then given by

$$\bar{n}_i = \sum_{n=5}^{15} n \cdot \alpha_{in} \ .$$

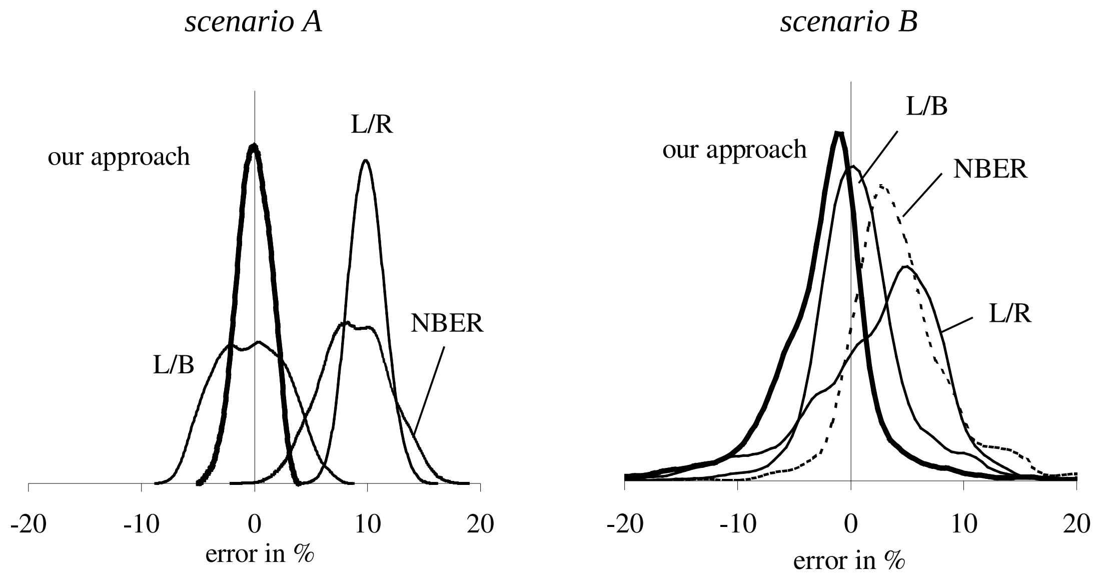
- We set book depreciations equal to economic depreciations, so there is no need to correct non-economic, tax-oriented depreciations. (Note that this assumption has to be made in the approaches by L/R, NBER and L/W, while in our algorithm we make use of an adjustment procedure in the initial year to correct for differences and apply an economic meaningful linear depreciation scheme.)

  A. Equal investment throughout all years, price increases randomly drawn from a uniform distribution between 0 and 10 % per year.

  B. Random draws from the empirical data (Bilanzstatistik/VGR)

According to this procedure, the true capital stock at replacement values is generated for a period of 70 years. We assume that the data available to the researcher start at period 21 (=t_0).

Figure 2: Distribution of errors for the different algorithms (estimation period 30 to 50, age of firms at initial estimation is 20 years, 1000 firms)



Notes: L/R = Lindenberg and Ross, L/B = Lewellen/Badrinath. We use kernel-density estimates (triangular kernel, bandwidth 1 %).

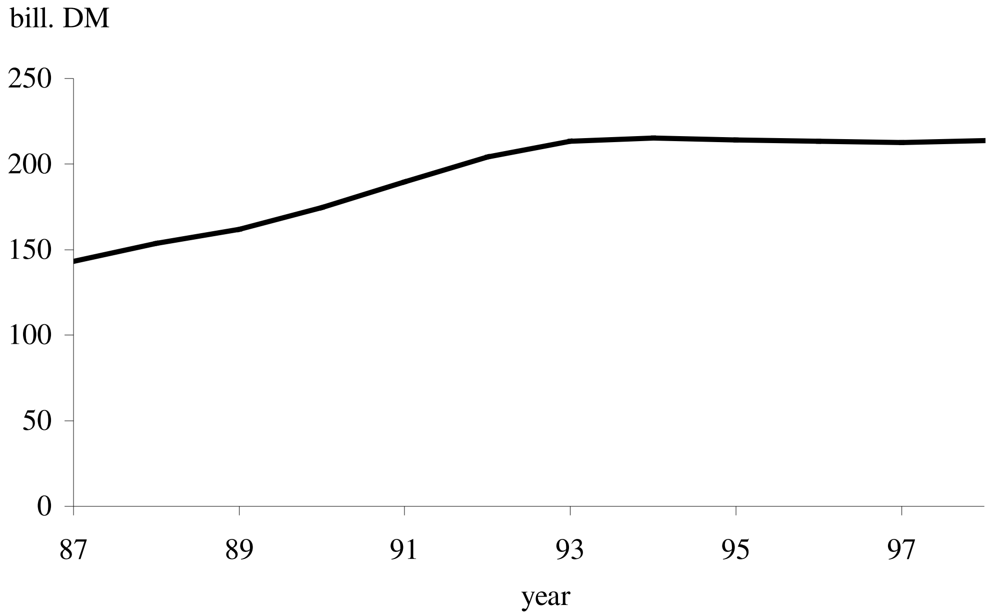
It can be seen from the simulation results that the algorithm we propose performs rather well. The results show that our algorithm is outperformed by the algorithm suggested by Lewellen/Baldrinath. But it should be remembered that their approach requires investment to be known at least 10 years before the first capital stock can be calculated. Therefore their approach, even having the smallest error, cannot be applied in most empirical cases. Comparing the algorithm which we propose with the two approaches having similar data requirements, we find that the errors for the new algorithm are rather small.

4.4. Estimates of the capital stock

4.4.1. The capital stock at replacement costs for the Bundesbank data file

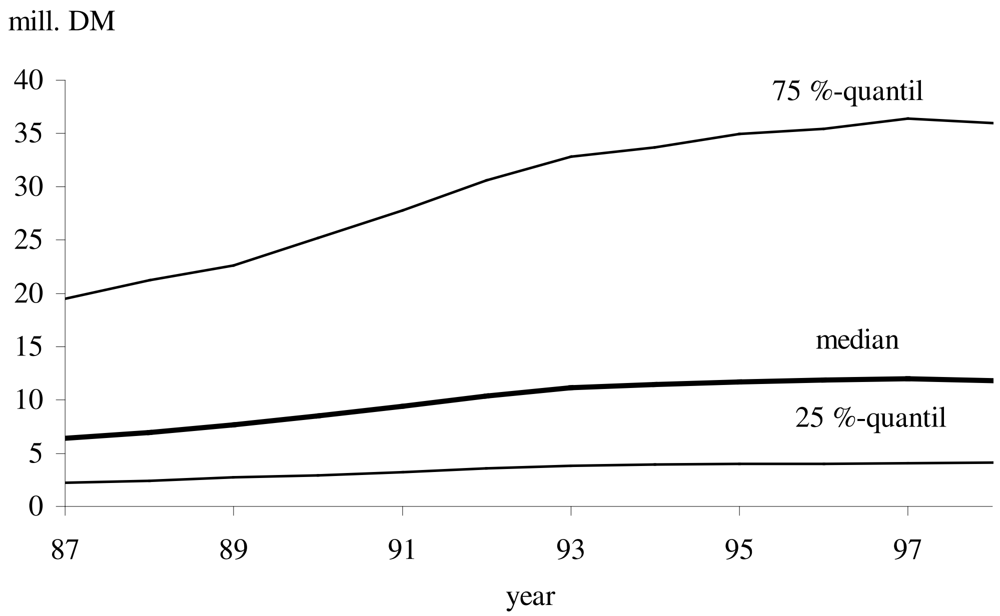
If we summarize the results, we find that the ratio of the capital stock at replacement costs to balance sheet values at historical costs is on average 2.5. There is a strong increase in the capital stock at replacement values by about 25% between 1987 and 1993. In the following years up to 1998 the capital stock is almost stationary.

Figure 3: Sum of calculated capital stocks at replacement values



If we estimate median and quartiles it is apparent that the distribution of the capital stocks of individual firms is extraordinary skewed. The median of the capital stock in our data base is about 10 million DM.

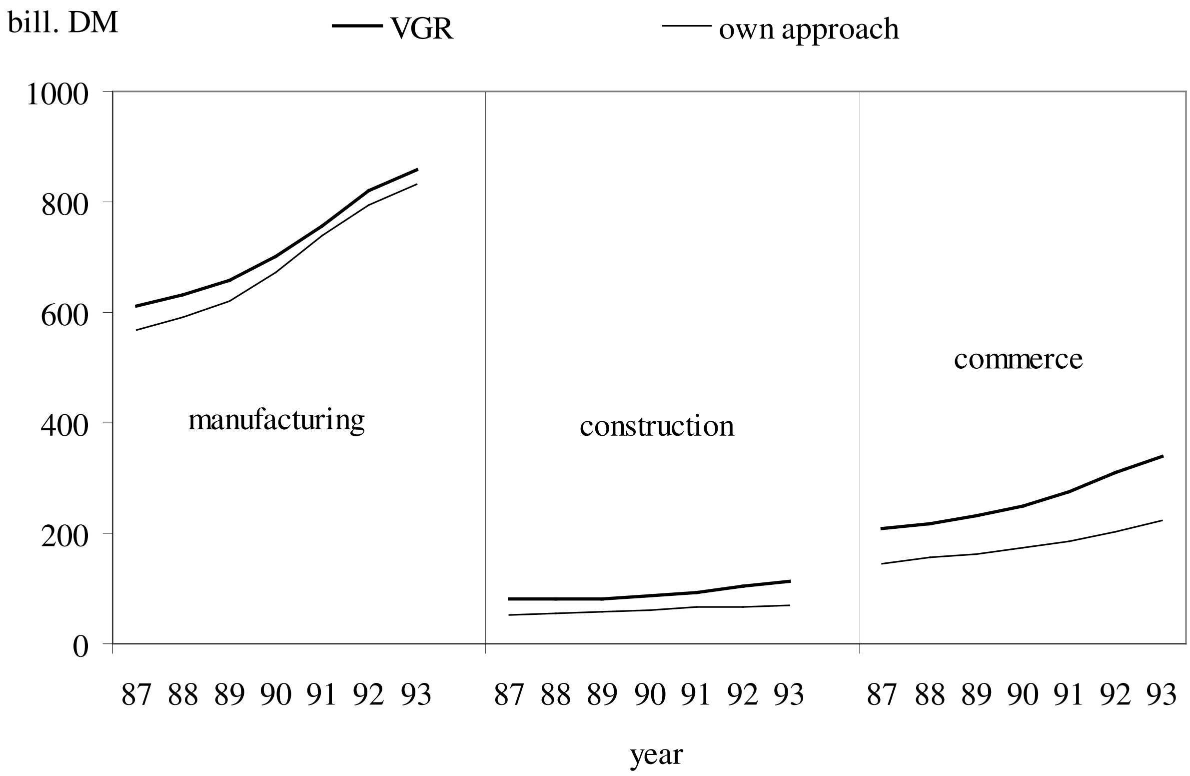
Figure 4: Level and dispersion of the capital stocks



4.4.2. A comparison with official sectoral data

For calculating sectoral capital stocks based on the individual balance sheet data, we expand the sectoral estimates proportionally by the ratio of the sum of sales to the sectoral sales figures.

Figure 5: Estimates by proportional expansion through sales



The comparison with official sectoral data (national accounts) shows that for manufacturing and construction the estimates based on the individual balance sheet data resemble the aggregate data reasonably well. Only for the wholesale/retail trade sector do the balance sheet-based figures underestimate the sectoral data noticeably. When assessing the results it should be borne in mind that no information concerning the sectoral level of capital stocks was used in the calculations. Only sectoral price changes and sectoral ratios of different price concepts were used for adjusting the book values as well as the sales coverage ratio of our data base. We therefore conclude that the algorithm used for estimating the capital stock at replacement values based on given historical cost data from firm-level balance sheets performs rather well.

5. The Calculation of *Q*

While the advantage of average *Q* based on stock prices is the exploitation of market expectations there are several serious drawbacks to this conventional approach. First, market expectations can be rather poor. The recent slump in technology shares, which lost about 90% of their value within one year, may serve as an example of the noisiness of share prices. The second drawback is that only a small fraction of an economy's firms is quoted on stock markets. Finally, it is marginal *Q* that is theoretically relevant for the firm's investment decision and not average *Q*, except under special conditions concerning production technology.

In this chapter we outline our approach to calculating measures of *Q* using balance sheet data. Both measures of *Q* we calculate are based on balance sheet data using a vector-autoregressive forecasting procedure. By estimating market values of equity, we first calculate average *Q* values comparable to the conventional *Q* measures based on stock markets. In a second approach following Gilchrist and Himmelberg (1995, 1998) we estimate marginal *Q*-values based on strong assumptions about firms' production technology. After giving a brief overview of related work, the estimation procedure as well as empirical results are presented.

5.1. An Overview of empirical work using the direct forecasting approach

In the following overview we concentrate on empirical papers which adopt the direct forecasting approach. An extensive overview of empirical studies using stock market data was already provided by Hubbard (1998). We start with the influential paper by Abel and Blanchard (1986), which introduced the method of vector autoregression into the context of *Q*-models. Even though it only used aggregated data, the paper laid the fundamental basis for the following extensions to panel data by Gilchrist and Himmelberg (1995, 1998). The paper by Bontempi et al (2001) follows Gilchrist and Himmelberg by applying the approach to a large panel data set of non-quoted Italian firms.

5.1.1. Abel/Blanchard (1986)

Abel and Blanchard base their approach on the *Q*-theory of investment. Instead of using the conventional stock market-based average *Q*, they estimate *Q* through forming expectations on future returns based on lagged variables.[12] The authors use a VAR model to make use of the time series information contained in their macroeconomic data set. Marginal *Q* is estimated as the discounted sum of expected future profits.[13] The expectations of the unknown marginal profits and the unknown discount factors are each estimated as linear combinations of an observable vector *Z* which evolves according to a

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12 See Abel/Blanchard (1986), p. 249.

13 Thereby Abel and Blanchard treat the future discount rate as an unknown random variable. In this case the estimation of the unknown marginal *Q* requires taking into account the product of random variables.

vector-autoregressive process. As the information set Ω_{t-1} includes only lagged values of *Z*, the estimated *Q* is a beginning-of-period marginal profit of investment.[14]

Variables used to estimate the VAR are, besides the returns on equity and debt, the ratio of labor cost to the capital stock, the sales/capital stock ratio, the stock market valuation of capital, average *Q*, the manufacturing price inflation, and the investment ratio.

In the estimated investment functions, only lagged values of the estimated marginal *Q* series have any explanatory power for investment, whereas the parameter of current *Q* is insignificantly negative. If added to the investment equation, lagged sales appear to have a significant positive influence on investment.

The performance of marginal *Q* in explaining the investment ratio is relatively poor. The authors present a list of possible causes of the poor results: the aggregation problems, the assumption of homogeneity of capital, the assumption of perfect capital markets and the negligence of liquidity constraints.

5.1.2. Gilchrist/Himmelberg (1995, 1998)

Following Abel and Blanchard (1986), the authors estimate a set of vector-autoregressive forecasting equations using a subset of balance sheet information. The forecasts of the VAR model are used to construct the expected value of marginal *Q* conditional on the observed fundamentals. The expected value of marginal *Q* is called fundamental *Q*.[15]

The unobservable marginal profit of capital is proxied by a measure of realized profits in relation to the existing capital. This approximation holds under strong assumptions concerning the production technology.[16]

The VAR model is estimated separately for a priori liquidity constrained and unconstrained firms to allow for differences in the forecasting scheme. The authors do not use firm-specific depreciation rates nor time-varying interest rates. The fixed value assumed for depreciation is 15% and the fixed value assumed for the interest rate is 6%.

Tobin's *Q* based on share prices leads to much lower parameter estimates compared to fundamental *Q*. Adding cash flow as a further explanatory variable leads to a significant cash flow sensitivity for both *Q* specifications. When the sample is grouped a priori, only the constrained firms show a significant cash flow sensitivity. Controlling for cash flow through the incorporation in the forecasting system does not alter the findings of the previous literature.

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14 Abel and Blanchard use quarterly data on US manufacturing for the period 1948:2 to 1979:3. The VAR model is estimated using 5 or 7 variables following a fourth-order vector-autoregressive process.

15 In the 1998 paper Gilchrist and Himmelberg extend the approach, analyzing in a first step the dynamics of firms' investment behaviour using a VAR model for panel data. See Gilchrist/Himmelberg (1998).

16 See Gilchrist/Himmelberg (1995), p. 550.

Even if the authors find Tobin's Q a poor proxy for investment opportunities, the results of the literature using Tobin's Q are confirmed. The fundamental Q seems to be superior, leading to higher parameter estimates. Because cash flow is explicitly included in the forecasting model, the authors interpret an additional sensitivity of cash flow as evidence of the existence of capital market imperfections.

5.1.3. Bontempi et al (2001)

Bontempi et al base their analysis on the fundamental distinction between equipment and structures.[17] These two components of the capital stock are characterized by different rates of depreciation and a different tax treatment. The usual aggregation of equipment and structures is criticized because this aggregation rests on the counterfactual assumption of perfect substitutability. Further, the authors assume that equipment and structures show different adjustment costs.[18]

The results show that equipment reacts strongly and significantly to Q, whereas structures do not respond to Q.[19] Some of the regressions have to be interpreted with care because the Sargan test fails to reject the validity of the instruments. When testing for different forms of adjustment costs, the authors find that the assumption of convex adjustment costs does not hold for structures. This implies a fixed component in the adjustment costs. When estimating separate equations for purchases and sales of investment goods, the results show that only equipment responds significantly to Q, with purchases reacting much more strongly than sales.

In a further step Bontempi et al explore the possibility of interrelated adjustment costs. It is therefore assumed that the level of structures influences the adjustment costs of equipment and vice versa, and that the adjustment cost function is linearly homogeneous. The estimated investment functions now include, besides the Q-measures for equipment and structures, the ratio of the two components of the capital stock as well as the product of Q and the measure of the capital stock's structure. For this investment equations Q is significant for structures as well as for equipment, while the structure of the capital stock is never significant and the combined effect only sometimes. Based on these results, the authors conclude that the two capital goods seem to be complements in their adjustment costs.[20]

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17 See Bontempi et. al. (2001), p. 2.

18 The authors use a large database including balance sheets and income statements of more than 52,000 Italian manufacturing firms. The final estimates are base on a balanced panel of 1,539 firms.

19 See Bontempi et. al. (2001), p. 16.

20 See Bontempi et. al. (2001), p. 23.

5.2. The Calculation of *Q* using firm-level balance sheet data

We use the following definition of marginal *Q* stated by Hayashi (1982) as the starting point: "Remember that *Q*, which we call marginal *Q*, is the ratio of the market value of an additional unit of capital to its replacement cost."[21]

As marginal *Q* is not observed, one way to overcome this problem followed extensively in the empirical literature is to use stock market data to measure unobservable expectations. Since in Germany only the smallest share of an economy's firms is quoted on stock markets, the concept of using stock market data to study firms' investment behaviour excludes the majority of firms from an empirical investigation.[22] When using accounting data it is therefore necessary to apply alternative concepts to find measures that proxy for the expectations about future profits or future marginal profitabilities of capital. In the following two concepts for measuring the firm's investment profitabilities, average *Q* and marginal *Q*, are illustrated.

5.2.1. Calculating Tobin's *Q* (average *Q*)

The approach used in this paper is based on the formula used by several authors[23] to calculate Tobin's *Q* for firm *i* at period *t* as the ratio of the market value of equity (V_{it}) plus the market value of outstanding debt (D_{it}) minus the replacement value of all remaining assets besides the capital stock (N_{it}) to the replacement value of the capital stock (K_{it}):

$$Q_{it} = \frac{V_{it} + D_{it} - N_{it}}{K_{it}}$$

When using balance sheet data in the empirical analysis, no market values of equity and debt are available in the data source and they therefore have to be estimated. The approach used in this paper is to estimate market values of equity based on a VAR-forecasting model as was suggested by Abel and Blanchard (1986). This approach was extended to panel data by Gilchrist and Himmelberg (1995, 1998).

The VAR-model we estimate contains three variables, pre-tax profits (*PTP*), sales (*S*) and cash flow (*CF*). The use of pre-tax profits instead of the theoretically more appealing after tax profits is inevitable because the apparent tax rate often shows implausible values and enormous variance. This is due to the fact that the data base contains firms of different legal status and no information about the firms' dividend policy. In our final estimates we make use of the forecasts based on a VAR containing one lag, but we obtained comparable results when using two lags.

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21 Hayashi (1982), p. 214.

22 Beside the argument of data availability, the empirical results using stock market data have been rather disappointing, see e.g. the overview in Chirinko (1993).

23 See e.g. Erickson/Whited (2000a) p. 1034.

The equations of the VAR model using one lag can be written as

$$x_{1it} = d_{1i} + a_{11}x_{1i,t-1} + a_{12}x_{2i,t-1} + a_{13}x_{3i,t-1} + \varepsilon_{1it}$$

$$x_{2it} = d_{2i} + a_{21}x_{1i,t-1} + a_{22}x_{2i,t-1} + a_{23}x_{3i,t-1} + \varepsilon_{2it}$$

$$x_{3it} = d_{3i} + a_{31}x_{1i,t-1} + a_{32}x_{2i,t-1} + a_{33}x_{3i,t-1} + \varepsilon_{3it}$$

The equations of the VAR do not contain time dummies because we are interested in expected values conditioned on lagged values and fixed firm effects and not conditioned on specific time effects.[24]

As the usual LSDV estimator is known to be biased, one of the various other available approaches has to be followed, taking into account the problems of dynamic panel data estimation.[25] When applying a direct bias correction to estimate the dynamic equations containing fixed effects, all variables *j* are measured as deviations from their firm-individual means and therefore the equations do not contain firm-specific effects:

$$\tilde{x}_{jit} = x_{jit} - \frac{1}{T}\sum_{t=1}^{T} x_{jit}$$

Alternatively the dynamic equations can be estimated using a GMM approach. In this case differencing leads to the elimination of the firm-specific effects:

$$\Delta x_{jit} = a_{j1}\Delta x_{ji,t-1} + a_{j2}\Delta x_{ji,t-1} + a_{j3}\Delta x_{ji,t-1} + \Delta\varepsilon_{jit}$$

In the following we drop the tilde (the difference operator respectively) to ease readability.

In short notation the system of (seemingly) unrelated equations can be written as

$$\mathbf{x}_{it} = \mathbf{A}\mathbf{x}_{i,t-1} + \boldsymbol{\varepsilon}_{it}$$

Assuming a stationary process for each point of time *t*, the one-period-ahead forecast can be estimated by

$$\hat{\mathbf{x}}_{i,t+1} = E\left[\mathbf{x}_{i,t+1} \mid \mathbf{x}_{it}\right] = \hat{\mathbf{A}}\mathbf{x}_{i,t}$$

The two-period-ahead forecast can be estimated using the one-period-ahead forecast

$$\hat{\mathbf{x}}_{i,t+2} = E\left[\mathbf{x}_{i,t+2} \mid \mathbf{x}_{it}\right] = \hat{\mathbf{A}}\hat{\mathbf{x}}_{i,t+1}$$

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24 When time effects are included forecasts have to build upon special assumptions concerning the unknown future time effects.

25 See Nickell (1981).

and so on.[26]

Using these forecasts, the discounted value of future profits at time t can be calculated as follows, where it is assumed that profit is the first of the three variables used in the VAR[27]:

$$V_{i,t} = \sum_{\tau=1}^{\infty} E\left[x_{1i,t+\tau} \mid \mathbf{x}_{it}\right] \delta_{t,\tau}^{\tau}$$

$$\hat{V}_{i,t} = \sum_{\tau=1}^{\infty} \hat{x}_{1i,t+\tau}\, \delta_{t,\tau}^{\tau}$$

$$\text{with } \delta_{t,\tau}^{\tau} = \frac{1}{(1+r_{t,\tau})^{\tau}}.$$

We use the capital market interest rate (Umlaufsrendite festverzinslicher Wertpapiere inländischer Emittenten) as a measure of the opportunity costs to discount future profits. For each year the firm faces its forecasting problem, we use the actual term structure of capital market interest rates for 1 to 9 years maturity. For discounting even further forecasts the interest rate with a maturity of 9 years is used. In this respect we differ from earlier approaches (Gilchrist and Himmelberg 1995, 1998 and Bontempi et. al. 2001), which for simplicity assume a fixed interest rate for all years and for all maturities.

The estimated discounted value of future profits $\hat{V}_{i,t}$ is taken as part of the nominator to calculate firm and year-specific average *Q:*

$$Q_{it}^{a} = \frac{\hat{V}_{it} + D_{it} - N_{it}}{K_{it}}$$

5.2.2. Calculating marginal *Q*

So far we have estimated average Q^a using the estimated market value of equity.[28] To calculate marginal (fundamental) Q^m we follow a similar approach using the described Panel-VAR-technique. To calculate fundamental Q^m we first have to find a proxy for the marginal profitability of capital (MPK_{it}). Following Gilchrist and Himmelberg (1998) we use a measure based on a Cobb-Douglas-Production technology where capital is seen as a quasi fixed factor of production:

$$Y = CK^{\alpha}L^{\beta}M^{\gamma}$$

26 This formulation of the forecast process does not take into account the existence of individual fixed effects. Either these effects have to be cancelled out by some data transformation (averaging or differencing) or they have to be estimated explicitly. See the Appendix for further details.

27 In our calculation we stop after 200 forecasting periods instead of using an indefinite forecast horizon.

28 From a theoretical point of view a marginal *Q* is more appropriate, see Gilchrist/Himmelberg (1998).

with

Y	output
K	capital stock
L	labour
M	intermediates
α, β, γ	elasticities of production

Allowing for economies of scale

$$\alpha + \beta + \gamma = 1 + \lambda ,$$

the firm faces the following maximization problem:

$$\pi = YP - LW - MV - F$$

with

π	profit
P	output price
W	wage
V	price of intermediates
F	fixed costs

subject to the Cobb-Douglas production function

$$\pi = AK^{\alpha} L^{\beta} M^{\gamma} P - LW - MV - F \ .$$

The marginal profitability of capital is given by

$$\frac{\partial \pi}{\partial K} = \frac{\partial \left(AK^{\alpha} L^{\beta} M^{\gamma} P - LW - MV - F \right)}{\partial K}$$

Allowing for non-perfect competition, the *MPK* can be written as

$$= \frac{\partial Y}{\partial K} P + \frac{\partial P}{\partial Y} \frac{\partial Y}{\partial K} Y = \frac{\partial Y}{\partial K} P + \frac{\partial P}{\partial Y} \frac{Y}{P} P \frac{\partial Y}{\partial K} = \frac{\partial Y}{\partial K} P + \eta^{-1} P \frac{\partial Y}{\partial K}$$

$$= \frac{\partial Y}{\partial K} P(1 + \eta^{-1}) = \alpha K^{-1} YP(1 + \eta^{-1}) = \alpha (1 + \eta^{-1}) \frac{S}{K} = \theta \frac{S}{K}$$

with

η price-elasticity of demand

S sales

Therefore, the unknown *MPK* is proportional to the sales-to-capital-stock ratio. To estimate the unknown parameter θ we assume that on average the *MPK* equals the user costs of capital (*U*), which we measure as the sum of the apparent interest rate (r_i) and the rate of depreciation (d_i). Using the sectoral calculation of θ including all years and all firms belonging to sector *j*

$$\hat{\theta}_j = \frac{\overline{U}_j}{\overline{\left(\frac{S}{K}\right)}_j} = \sum_{i \in I(j)}^{N_j} \sum_{t=1}^{T} (r_i + d_i) \cdot \left[\sum_{i \in I(j)}^{N_j} \sum_{t=1}^{T} \left(\frac{S}{K}\right)_{it} \right]^{-1}$$

the firm and year-specific marginal profitability of capital is estimated as

$$\widehat{MPK}_{it} \approx \hat{\theta}_j \left(\frac{S}{K}\right)_{it}$$

Marginal *Q* is then calculated as the present value of estimated future marginal profitabilities of capital

$$Q_{i,t}^{m} = \sum_{\tau=1}^{\infty} E(MPK_{it}) \delta_{i,t,\tau}^{\tau} \approx \hat{\theta}_j \sum_{\tau=1}^{\infty} \left(\frac{S}{K}\right)_{i,t+\tau} \delta_{i,t,\tau}^{\tau}$$

$$\text{with } \delta_{i,t,\tau}^{\tau} = \frac{(1+d_i)^{\tau}}{(1+r_{t,\tau})^{\tau}}$$

where the market interest rate for the relevant maturity and firm specific depreciation rates are used.[29] The estimated VAR model with one lag includes the estimated *MPK*, the cash flow (*CF*) and the operating income (*OI*), both measured as the ratio to the capital stock.

29 While Gilchrist and Himmelberg (1995) assume a constant value for all firms and all years we take the individual depreciation rates, resulting mainly from different ratios of structure to equipment for individual firms, as well as the interest term strucuture into account.

6. Empirical Results

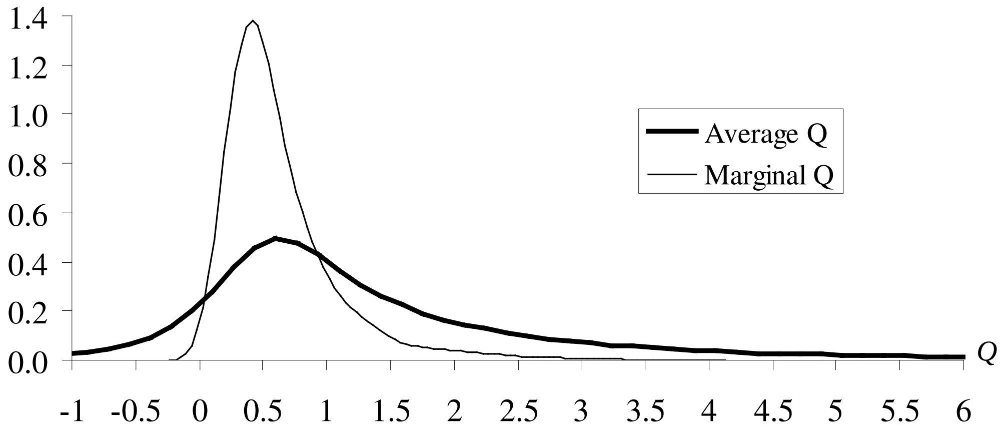
6.1. Descriptive evidence

The following table contains some descriptive statistics for the estimated average and marginal *Q*. From the table as well as from the graph containing kernel-density estimations for the two *Qs*, it can be seen that average *Q* exhibits on average a higher level and greater variance.[30] While the average *Q* is somewhat higher than the expected equilibrium value, the estimated marginal *Q* values are somewhat too low.

Table 1: Descriptive statistics of the estimated Qs

Q	*n*	$\overline{X}$	*Median*	$Q_{25\%}$	$Q_{75\%}$	σ	*Skewn.*
Average *Q*	23,030	1.38	0.96	0.43	1.86	1.61	2.08
Marginal *Q*	23,030	0.63	0.51	0.34	0.78	0.45	2.20

Figure 6:Kernel-density estimations for the estimated Qs

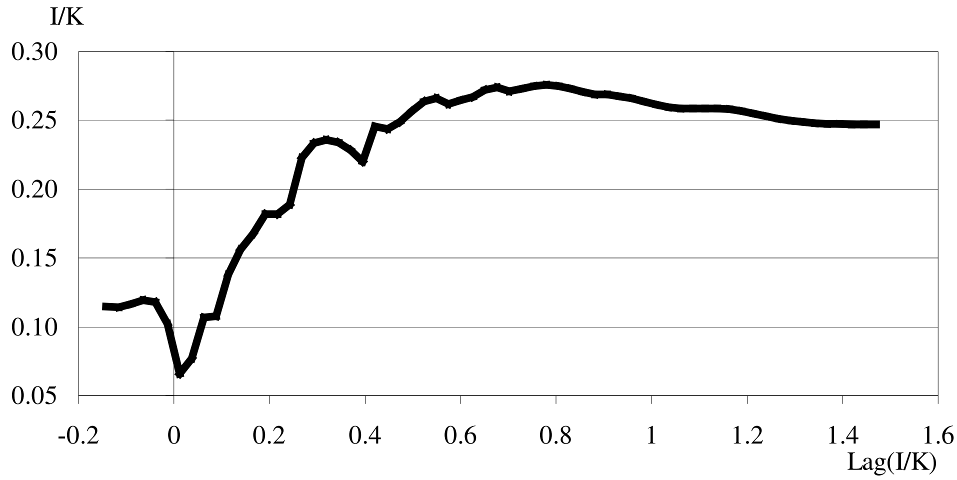


Note: The kernel used was triangular with a bandwidth of 0.25.

Before estimating the dynamic investment equations using the two different measures of *Q* we take a non-parametric approach to see whether we can find any indication of a linear relation in the bivariate case. We estimate three non-parametric regressions explaining the investment ratio by its lagged value, average and marginal *Q* respectively.

30 To control for outliers we drop the upper and lower 0.5% quantils for both (average and marginal) *Q*-measures.

Figure 7: Kernel regression: I/K = f(I/K $_{-1}$)

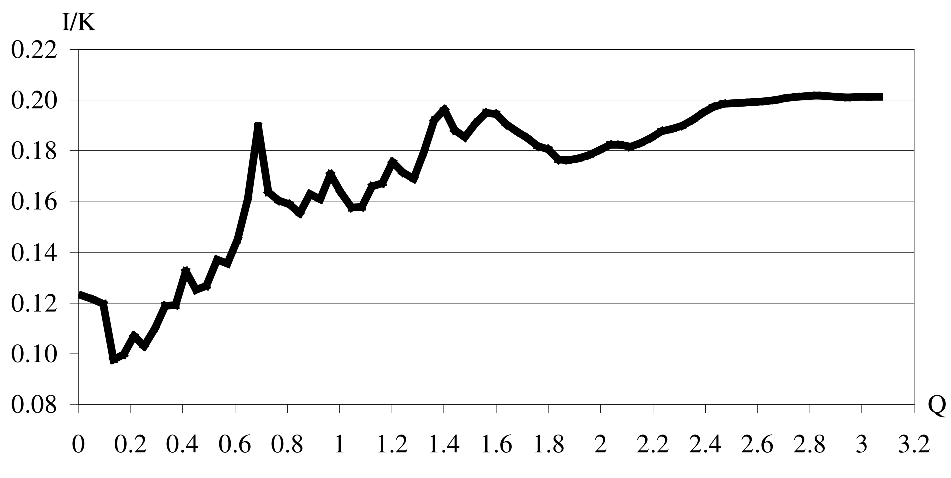


Note: The non-parametric regression includes the 500 nearest neighbours at each data point. The kernel used was triangular.

Figure 8: Kernel regression: I/K = f(Q^a)

Note: The non-parametric regression includes the 500 nearest neighbours at each data point. The kernel used was triangular.

Figure 9: Kernel regression: I/K = f(Q^m)



Note: The non-parametric regression includes the 500 nearest neighbours at each data point. The kernel used was triangular.

The non-parametric regression indicates a positive and fairly linear relation between investment and the Q measures for positive Q-values, while the figure for lagged investment might indicate a saturation point.

6.2. Estimated Q-investment functions

The investment functions are estimated using a bias-corrected estimator to take into account the resulting bias when using the lagged endogenous variable.[31] We also applied GMM-estimation techniques to estimate the dynamic investment function. But when comparing the two estimation techniques we prefer the direct bias correction method for two reasons. First, when analyzing different estimator simulation studies (Kiviet (1995), Judson and Owen (1999), Hansen (2001)) find a corrected LSDV estimator superior compared to GMM-estimators.

Second, as is usually the case when using large micro data files containing mainly cross-section information, the correlations of the data are rather low in almost all respects. Therefore, the use of differences instead of levels considerably reduces the amount of information contained in the data used for estimation. Instrumental estimation is known to be problematic when instruments are rather weak.[32] When instruments are weak, the results are extremely sensitive to the choice of instruments, leading to a large number of degrees of freedom for the researcher. We therefore regard it as an advantage of the bias correction approach that it restricts these facilities.[33]

Average Q:

$$\widehat{\left(\frac{I}{K}\right)} = a_i + \underset{(18.38)}{0.121}\left(\frac{I}{K}\right)_{-1} + \underset{(35.95)}{0.070}\ Q^a_{-1} \qquad n = 23{,}030$$

Marginal Q:

$$\widehat{\left(\frac{I}{K}\right)} = a_i + \underset{(7.23)}{0.051}\left(\frac{I}{K}\right)_{-1} + \underset{(27.62)}{0.299}\ Q^m_{-1} \qquad n = 23{,}030$$

We find both measures of Q to be highly significant.[34] In both equations the lagged investment ratio is highly significant as well. Comparing the parameters, we find that the parameter of marginal Q is four times the parameter of average Q. But it has to be taken into account that average Q has a standard deviation almost four times the standard

31 See the appendix for details about the estimation procedure.

32 When instrumenting the difference of Q by the lagged difference of Q we loose about 99% of the information contained in the difference of Q!

33 A comparison of the results using GMM-methods is given in the appendix.

34 These results confirm the significant influence of Q on German firms investment spending found when using sectoral data, see Behr/Bellgardt (1998, 2000). For results for German firms using stock market data see Audretsch/Elston (2002).

deviation of marginal Q. The parameter of average Q is at the upper bound of the interval of parameters found in empirical studies using stock market data rather than the direct forecasting approach.[35] The higher parameter of marginal Q is closer to the theoretical expectations about its value when trying to interpret the parameter as the capital stock adjustment cost parameter. However, because of the dependence of the parameter value on the standard deviation of the Q measure, the parameter should be interpreted with care. Whited (1992) discusses the problems of inferring adjustment cost parameters from the Q-parameter in detail.

Even if the simple variance decomposition does not hold exactly in the context of the dynamic panel data estimation, the share of explained variance is still a useful indicator of the explanatory power of the estimated equation. It turns out that average Q (5%) explains a slightly larger part of investment compared to marginal Q (4%).

As marginal and average Q were measured quite differently, one might ask whether the information is rather redundant, or whether the two measures are independent of one another. As shown by Hayashi (1982), the two measures can be interchanged only in the case of perfect competition and linear homogeneous technology.

Therefore, comparing the two different measures can also be seen as an indirect test of the combined hypothesis of the production function and the adjustment cost function of the capital stock being linearly homogeneous and of perfect competition. Of course, the comparison is based on the operationalisation of both concepts and therefore depends strongly on the adequacy of the operationalisation procedure. The following shows the estimated dynamic investment function containing marginal as well as average Q.

$$\widehat{\left(\frac{I}{K}\right)} = a_i + \underset{(6.49)}{0.044}\left(\frac{I}{K}\right)_{-1} + \underset{(37.21)}{0.070}\, Q^a_{-1} + \underset{(29.21)}{0.306}\, Q^m_{-1} \quad n = 23{,}030$$

We find that both measures of Q contain valuable and largely independent information explaining the investment behaviour of firms. According to the t-values, average Q does explain partially a somewhat larger amount of the investment compared to marginal Q. Together both measures of investment profitability explain about 10% of the variation of investment according to the naive measure of residual sum of squares divided by total sum of squares. The finding of fairly independent information in the two different measures of Q casts doubt on the theoretical assumptions of perfect competition and linear homogenous technology, which would make the use of the two measures interchangeable.

35 See e.g. Whited (1992).

6.3. Results for classes of firm size

In this section of the paper we analyse the investment behavior of four classes of firm size. The following table contains descriptive measures for these four classes of firm size.[36]

As can be seen, the investment ratio decreases with firm size from 16.6 % in the smallest class of firms to only 11.8 % in the class containing the largest firms. While marginal *Q* also decreases from 0.7 for the smallest firms to only 0.6 in the class of the largest firms, there is no such evidence for average *Q*.

Table 2: Descriptive statistics for class sizes
Averages, standard deviation in parentheses

	All	*class 1 (smallest)*	*class 2*	*class 3*	*class 4 (largest)*
n	23,030	5,760	5,760	5,760	5,750
$(I/K)_{i,t-1}$	0.138	0.166	0.141	0.129	0.118
	(0.17)	(0.21)	(0.18)	(0.16)	(0.11)
$Q^m_{i,t-1}$	0.631	0.714	0.611	0.595	0.604
	(0.45)	(0.54)	(0.42)	(0.41)	(0.42)
$Q^a_{i,t-1}$	1.379	1.335	1.396	1.418	1.366
	(1.61)	(1.63)	(1.64)	(1.58)	(1.57)
TA	151.795	4.529	12.543	31.915	558.901
	(1172.22)	(3.6)	(8.17)	(22.4)	(2298.35)

Next we estimate dynamic investment functions for the four different size-classes using a direct bias correction estimation method. The following table contains the results. It can be seen that the firms belonging to different classes exhibit strong differences in their investment behaviour. The influence of the lagged investment ratio increases from 0.05 for the class of smallest to 0.23 for the class of largest firms and is significantly different from 0 in all classes. Of course, it has to be borne in mind that the smaller the capital stock the less continuous will the investment process of a firm be according to pure aggregation effects. For larger firms the aggregation will smooth out such discontinuities. The parameter for average *Q* almost halves from 0.092 for the smallest firms to only 0.040 for

36 The variable used to classify firms according to size is total assets (*TA*, balance sheet total) in 1988, the year prior to the estimation period. Because only the balance sheet total is observable for lenders and outsiders, we do not correct the balance sheet total for the capital stock at replacement values. The grouping according to the balance sheet total corrected for the revaluation of the capital stock leads to no major changes in the results.

the largest firms. Therefore it can be stated that the larger the firms the more its investment ratio is influenced by its past investment behaviour and the less it takes the profitability, measured by average Q, into account.

When using marginal Q the findings for the different size classes are similar concerning the increasing influence of lagged investment for increasing firm size. For marginal Q there is less evidence of decreasing influence with firm size compared to average Q. Each of the four different size classes show a strong and significant reaction to marginal Q.

Table 3: Average Q investment functions for class sizes

	All	*class 1 (smallest)*	*class 2*	*class 3*	*class 4 (largest)*
n	23,030	5,760	5,760	5,760	5,750
$(I/K)_{i,t-1}$	0.121	0.054	0.142	0.172	0.231
	(18.38)	(4.19)	(10.77)	(12.78)	(17.91)
$Q^a_{i,t-1}$	0.070	0.092	0.073	0.064	0.040
	(35.95)	(21.10)	(16.83)	(17.67)	(15.26)

Table 4: Marginal Q investment functions for class sizes

	All	*class 1 (smallest)*	*class 2*	*class 3*	*class 4 (largest)*
n	23030	5760	5760	5760	5750
$(I/K)_{i,t-1}$	0.051	-0.008	0.049	0.102	0.178
	(7.23)	(-0.61)	(3.52)	(7.23)	(13.16)
$Q^m_{i,t-1}$	0.299	0.276	0.360	0.297	0.237
	(27.62)	(12.19)	(16.50)	(13.88)	(12.79)

7. Conclusion

In this paper we have analyzed the investment behaviour of German firms within the framework of the Q-theory. Facing two severe problems of non-adequate capital stock balance sheet data and non-available stock market data, alternative measures were applied.

Transforming the balance sheet figures of the capital stock less depreciations at historical costs into meaningful figures at replacement values was accomplished using a new algorithm. The disaggregation into structures and equipment, the disaggregation into vintages and the existence of different capital goods' lifetimes is taken into account.

Since anonymous individual firm balance sheet data were used, no stock market measure of *Q* is available. The data basis contained roughly 2,000 firms covering the twelve years for the period 1987 to 1998. By following the approach of Abel and Blanchard and Gilchrist and Himmelberg, measures of *Q* were derived making use of a vector-autoregressive model to forecast future profitability directly. Two different measures of *Q*, marginal and average *Q* were derived. Both, a direct bias correction method and the GMM approach, were applied to estimate the investment functions. Given the loss of information when turning to differenced variables, as also because simulation results favour a direct bias correction procedure, the direct bias correction method was preferred to the GMM approach.

The estimation results of dynamic investment equations show that the *Q* measures influence the firm's fixed investment spending significantly. When comparing the two *Q*-proxies, the average *Q* slightly outperforms marginal *Q*. This outcome might be due to the strong assumptions concerning the production technology underlying the calculation of marginal *Q* which are perhaps not met in reality.

When analyzing the investment behaviour in four different classes of firm size, we find that larger firms react less strongly to *Q* and more strongly to lagged investment.

Appendix

A. Sectors included in the analysis

No.	Sector	n
1	Manufacture of food products and beverages	112
2	Manufacture of textiles	79
3	Manufacture of textile products	19
4	Manufacture of wood and wood products	78
5	Manufacture of pulp, paper and paper products	58
6	Publishing and Printing	44
7	Manufacture of chemicals and chemical products	85
8	Manufacture of rubber and plastic products	128
9	Manufacture of other non-metallic mineral products	105
10	Manufacture of basic metals	89
11	Manufacture of fabricated metal products, except machinery and equipment	132
12	Manufacture of machinery and equipment n.e.c.	240
13a	Manufacture of electrical machinery and apparatus n.e.c.	96
13b	Manufacture of medical, precision and optical instruments	26
14	Manufacture of motor vehicles, trailers and semi-trailers	52
15	Construction	109
16	Wholesale trade and commission trade	559
17	Retail trade, Transport	292

B. The Estimated Vector-Autoregressive Models for Panel Data

Average *Q* Forecasting Equations

left-hand side variables

right-hand side variables		*PTP*	*CF*	*S*
	PTP	0.858 (111.42)	0.145 (17.57)	1.444 (37.05)
	CF	-0.007 (-2.81)	-0.019 (-6.73)	-0.138 (-10.25)
	S	-0.005 (-3.93)	0.024 (19.01)	0.996 (165.87)

PTP Pre-Tax-Profits, *CF* Cash Flow, *S* Sales.

Marginal *Q* Forecasting Equations

left-hand side variables

right-hand side variables		*MPK*	*CFK*	*OIK*
	MPK	0.839 (154.36)	0.446 (10.27)	-0.146 (-5.71)
	CFK	-0.003 (-8.99)	-0.01 (-4.03)	-0.015 (-10.42)
	OIK	-0.024 (-16.1)	0.217 (18.01)	0.743 (105.06)

MPK Marginal Profitability of Capital, *CFK* Cash Flow divided by the adjusted capital stock, *OIK* Operational Income divided by the adjusted capital stock.

C. Details of the estimation technique

A direct bias correction procedure

The procedure is based on Kiviet (1995) and Hansen (2001). The basic idea is to estimate the asymptotical bias of the least-squares-dummy-variable-model through a plug-in method. In the following $\hat{\rho}$ denotes the LSDV-estimator of the lagged endogenous variable, $\hat{\beta}$ the estimated vector of the remaining explanatory variables. The $\cup$ refers to de-meaned variables.

The term

$$\left(\underset{N \to \infty}{p\lim} \frac{1}{NT} \breve{y}'_{-1} \hat{\varepsilon}_{-1} \right)^{-1}$$

is approximated by

$$\frac{NT}{\hat{\varepsilon}'_{-1} \hat{\varepsilon}_{-1}}$$

$$\text{and } \frac{-\sigma_{\varepsilon}^2}{T(1-\rho)} \left(1 - \frac{1}{T} \frac{(1-\rho')}{T(1-\rho)} \right)$$

$$\text{by } \frac{-\hat{\sigma}_{\varepsilon}^2}{T(1-\rho)} \left(1 - \frac{1}{T} \frac{(1-\rho')}{T(1-\rho)} \right)$$

$$\text{with } \hat{\varepsilon}_{i,t-1} = \breve{y}_{-1} - \breve{X}\hat{\beta} \text{ and } \hat{\beta} = \left(\breve{X}'\breve{X} \right)^{-1} \breve{X}\breve{y}_{-1} .$$

Now we search for the parameter ρ, using a grid-search, which minimizes the quadratic difference between asymptotic and estimated bias:

$$\hat{\rho}_c : \underset{\rho}{Min} \left[Bias - B\hat{i}as \right]^2$$

$$\hat{\rho}_c : \underset{\rho}{Min} \left[(\hat{\rho} - \rho) - \frac{NT}{\hat{\varepsilon}'_{-1} \hat{\varepsilon}_{-1}} \frac{-\hat{\sigma}_{\varepsilon}^2}{T(1-\rho)} \left(1 - \frac{1}{T} \frac{(1-\rho')}{T(1-\rho)} \right) \right]^2$$

The estimated bias-corrected parameter $\hat{\rho}_c$ is used to approximate $\hat{\beta}_c$:

$$\underset{N \to \infty}{p\lim} (\hat{\beta} - \beta) = - \underset{N \to \infty}{p\lim} \left(\left(\breve{X}'\breve{X} \right)^{-1} \breve{X}\breve{y}_{-1} \right) \underset{N \to \infty}{p\lim} (\hat{\rho} - \rho)$$

$$\hat{\beta}_c = \hat{\beta} + \hat{\beta}(\hat{\rho} - \hat{\rho}_c)$$

D. GMM and LSDV Estimates

GMM

$d\left(\frac{I}{K}\right)_{i,t-1}$	$dQ^{a}_{i,t-1}$	$dQ^{m}_{i,t-1}$	Sargan	AR(2)	n
0.128	0.031		111	1.92	20727
(13.60)	(5.70)		[0.049]	[0.054]	
0.084		0.229	115.4	2.13	20727
(5.64)		(5.92)	[0.027]	[0.033]	
0.081	0.028	0.187	145	1.92	20727
(6.00)	(5.22)	(5.16)	[0.208]	[0.054]	

t-values in parentheses. Both GMM equations are estimated in differences, only lagged values of the right hand side variables are used as GMM instruments. Lagged investment and Qs were instrumented using GMM instruments. The upper and lower 0.1% quantiles of the *Q* values where eliminated to prevent the equations being influenced by outliers. t-values are shown below parameters in parentheses. The p-values for the Sargan-Test for overidentifying restrictions and the test for second-order autocorrelation are shown in brackets below the statistics.

LSDV

$$\widehat{\left(\frac{I}{K}\right)} = a_i + \underset{(6.35)}{0.022}\left(\frac{I}{K}\right)_{-1} + \underset{(36.06)}{0.069}\, Q^{a}_{-1} \qquad n = 23{,}030$$

$$\widehat{\left(\frac{I}{K}\right)} = a_i - \underset{(-7.82)}{0.054}\left(\frac{I}{K}\right)_{-1} + \underset{(32.72)}{0.352}\, Q^{m}_{-1} \qquad n = 23{,}030$$

$$\widehat{\left(\frac{I}{K}\right)} = a_i - \underset{(-7.97)}{0.054}\left(\frac{I}{K}\right)_{-1} + \underset{(37.35)}{0.070}\, Q^{a}_{-1} + \underset{(34.12)}{0.355}\, Q^{m}_{-1} \qquad n = 23{,}030$$

E. The data source

The data set after calculating the capital stock using the detailed schedule of fixed asset movements leaves us with 3,169 firms and 11 years to start with.

To prevent outliers biasing the results we drop the upper and lower 0.5 % of the observations of the following nine variables:

- ratio of aggregated investment to the aggregated capital stock
- ratio of investment in equipment to the capital stock of equipment
- ratio of investment in structures to the capital stock of structures
- ratio of pre-tax profits to the capital stock
- ratio of sales to the capital stock
- ratio of cash flow to the capital stock
- ratio of operating income to the capital stock
- marginal *Q*
- average *Q*.

The balancing of the data after eliminating the outliers leaves 2,303 firms in the sample. Owing to lags, the period available covers 10 years, 1989-1998.

Throughout the analysis we use (with one exception) all variables at nominal values. The reason for doing so is the use of ratios in the investment equation:

$$\left(\frac{\hat{I}}{K}\right) = a_i + \beta_1 \left(\frac{I}{K}\right)_{-1} + \beta_2\, Q_{i,t-1}^{a}$$

By dividing through the capital stock, the resulting ratios contain the relevant information for the investor according to our understanding. We do not see a ratio of, for examples ales at prices of year *t-k* to the capital stock at prices of year *t-k* as constituting a relevant piece of information for the investor. By the same reasoning, we do not envisage an investor deciding about investment at prices of year *t-k* divided by the capital stock at prices of year *t-k*.

F. The forecasting procedure

For ease of presentation, we dropped the individual firm dummy variables in the text. The forecasting procedure takes these dummy variables into account:

$$\hat{\mathbf{x}}_{it} = \mathbf{A}\hat{\mathbf{x}}_{i,t-1} + d_i$$

$$\hat{\mathbf{x}}_{it} = \mathbf{A}\lfloor \mathbf{A}\hat{\mathbf{x}}_{i,t-2} + d_i \rfloor + d_i$$

$$\hat{\mathbf{x}}_{it} = \mathbf{A}\lfloor \mathbf{A}\lfloor \mathbf{A}\hat{\mathbf{x}}_{i,t-3} + d_i \rfloor + d_i \rfloor + d_i$$

$$\hat{\mathbf{x}}_{it} = \mathbf{A}\lfloor \mathbf{A}\lfloor \mathbf{A}\lfloor \mathbf{A}\hat{\mathbf{x}}_{i,t-4} + d_i \rfloor + d_i \rfloor + d_i \rfloor + d_i$$

$$\vdots$$

$$\hat{\mathbf{x}}_{it} = \mathbf{A}^s\hat{\mathbf{x}}_{i,t-s} + d_i \sum_{l=0}^{s-1} \mathbf{A}^l$$

where

$$E(\mathbf{x}_{it}) = E(\mathbf{A}\hat{\mathbf{x}}_{i,t-1} + d_i + u_i) = \mathbf{A}\hat{\mathbf{x}}_{i,t-1} + d_i$$

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