Chapter 2 – Financial Constraints and Capacity Adjustment: Evidence from a Large Panel of Survey Data

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Abstract:

The focus of this study is on two issues: (i) the interaction between financial constraints and capacity restrictions in general, and (ii) the difference between large and small firms. Using the CBI Industrial Trends Survey, we have detailed information on the financial constraints faced by a large sample of UK manufacturers. We develop a new identification scheme for financial constraints based on the link between financial constraints and the prevalence and duration of capacity gaps. Two important results emerge: First, financially constrained firms take longer to close capacity gaps. This indicates that financial constraints do indeed play a part in the investment process. Second, small firms close capacity gaps faster than large firms do, but financial constraints seem to be of greater relevance to their adjustment dynamics..

Keywords: Financial constraints, investment, capacity adjustment, small firm finance, duration analysis.

JEL-Classification: D21, D92, C33, C41

Chapter 2 – Financial Constraints and Capacity Adjustment: Evidence from a Large Panel of Survey Data

1 Introduction

Firms' activities are financially constrained if internal finance is insufficient and external finance is either relatively costly, carrying an external finance premium, or rationed. Understanding the causes and effects of financial constraints is of key importance for a variety of policy issues: monetary transmission, financial stability and growth and development, to name a few. Financial constraints are market imperfections that arise from information asymmetries between the providers of capital and firm owners or managers. Both agency problems and adverse selection are relevant. Therefore, small firms are deemed especially vulnerable, and the effects financial constraints have on firm-level real activity may well differ according to size. If this is true, the reaction of the economy to financial and monetary shocks will depend on the size composition of the firm sector. This paper aims to promote our understanding of the interaction between financial constraints and real activity, with a special focus on the differences that may exist between large and small firms.

Very little information on small firms can be gathered from micro-data sets based on quoted companies. For this study of UK manufacturing companies, we explore the data base for the CBI Industrial Trends Survey (ITS), which is an important survey for business cycle analysis in the United Kingdom. Apart from its size and coverage, the data set has two important characteristics. First, it contains many small firms. More than 63% of the ITS observations refer to firms with less than 200 employees. Second, there is direct information on the financial constraints that firms face in their investment decisions. Notably, a number of firms explicitly state two things: that they are constrained by the lack of either internal or external financial resources, and that these constraints have an influence on their investment behaviour.

This is exactly what the bulk of the empirical literature on financial constraints, following the seminal article by Fazzari, Hubbard and Petersen (1988), tries to prove. The standard procedure in this literature is to split the sample by some criterion that identifies *a priori* firms as being financially constrained or unconstrained, such as size, dividend behaviour or the risk of default, and then to test whether the observed differences in investment behaviour between the two types of firm are consistent with what is to be expected based on a better or worse financial standing in a situation of asymmetric information. This is done by comparing the sensitivity of investment with respect to internal cash flow.[1] Armed with the CBI data, we do not need this complicated and very indirect procedure, heavily criticised on theoretical grounds by Kaplan and Zingales (1997, 2000) and others: a subset of respondents explicitly claim to be constrained.

For the identification of financial constraints, we do not rely on comparing cash flow sensitivities. Instead, in line with Basu and Guariglia (2002) and Chapter 1, we focus on the dynamics of adjustment, which should be more protracted when firms are financially constrained. Specifically, we study capacity adjustment. First, we look at the *association* between two types of constraints: capacity restrictions and financial constraints, and then we undertake a *duration analysis* with respect to spells of capacity restrictions. Firms report whether their capacity is insufficient with respect to demand. Those firms which indicate financial constraints should take longer to close a capacity gap if there is informational content in their answers – either because they are less able to finance their investments or else because they have bigger gaps to fill. To the best of our knowledge, the duration of capacity constraints has never been investigated before at a micro-econometric level.

Our identification of financial constraints is discussed in Section 2. Section 3 presents the data set and some descriptive statistics. The raw percentages do not show small firms as being particularly strongly affected by financial constraints. Although the severest form of financial constraints – inability to raise external finance – is more prevalent among small firms (5.1% compared with 3.0% for the other size groups), the share of small firms reporting inadequate internal finance is actually slightly smaller (18.2% as against 20.4% for all other size groups).

Section 4 contains our statistical test results. For both size classes, we find a strongly significant contemporaneous association between the two types of constraints. With respect to duration, financially constrained firms do take longer to end a period of insufficient capacity. However, splitting the sample shows that the latter relationship is sta-

[1] See, for example, Chirinko and von Kalckreuth (2002).

tistically significant only for small firms. For larger firms, the measured difference in duration is less marked and not significant at conventional levels. It is quite interesting to see that small firms appear to be able to overcome their capacity shortfalls faster than larger firms – both in general and conditional on their financial status. The paper ends with a conclusion in Section 5.

2 Identifying the effects of financial constraints

As highlighted further down, a sizeable proportion of firms in the CBI Industrial Trends Survey state that their investment is constrained either by insufficient internal funds or by the inability to raise external finance. The question on constraints on investment is of key importance for our study. We therefore quote the exact wording here:

Question 16c: What factors are likely to limit (wholly or partly) your capital expenditure authorisation over the next twelve months? *(If you tick more than one factor, please rank in order of importance)*

- inadequate net return on proposed investment
- shortage of internal finance
- inability to raise external finance
- cost of finance
- uncertainty about demand
- shortage of labour, including managerial and technical staff
- other
- n/a

These statements are interesting and potentially very rich: as we shall see below, they permit the identification of the financial regime of a firm. Weighted averages of survey questions are often used for forecasting and evaluation purposes on a sectoral or macro level and in many cases turn out to be surprisingly accurate. Using CBI data, Mitchell, Smith and Weale (2002a, b) show that survey responses contain information that is useful in generating indicators of manufacturing output. Furthermore, they show that disaggregated indicators for output growth can outperform traditional aggregated measures with respect to their predictive content. However, it is not clear *a priori* how well the survey responses reflect the individual financial situation of the answering firm. Therefore, it is necessary to check the informational content of the statements on financial constraints at a micro level. In other words, we want to see whether the statements on financial constraints relate to other information in the data set in a way that is consistent with theory.

This, however, is no easy task. With asymmetric information there will be a premium on external financing over and above a fair default premium which simply compensates for the fact that the debtor will not have to pay in certain states of nature. The creditor is less able than the debtor to evaluate the situation of the firm and the prospects of the investment project. The finance premium covers expected dead-weight losses caused by monitoring, costs of litigation, adverse selection and moral hazard. But capital accumulation and financial constraints are determined simultaneously: financial constraints depend not only on the financial situation of the firm, but also on the *size of the planned investment.*

Figure 1: Capital demand and external finance premium

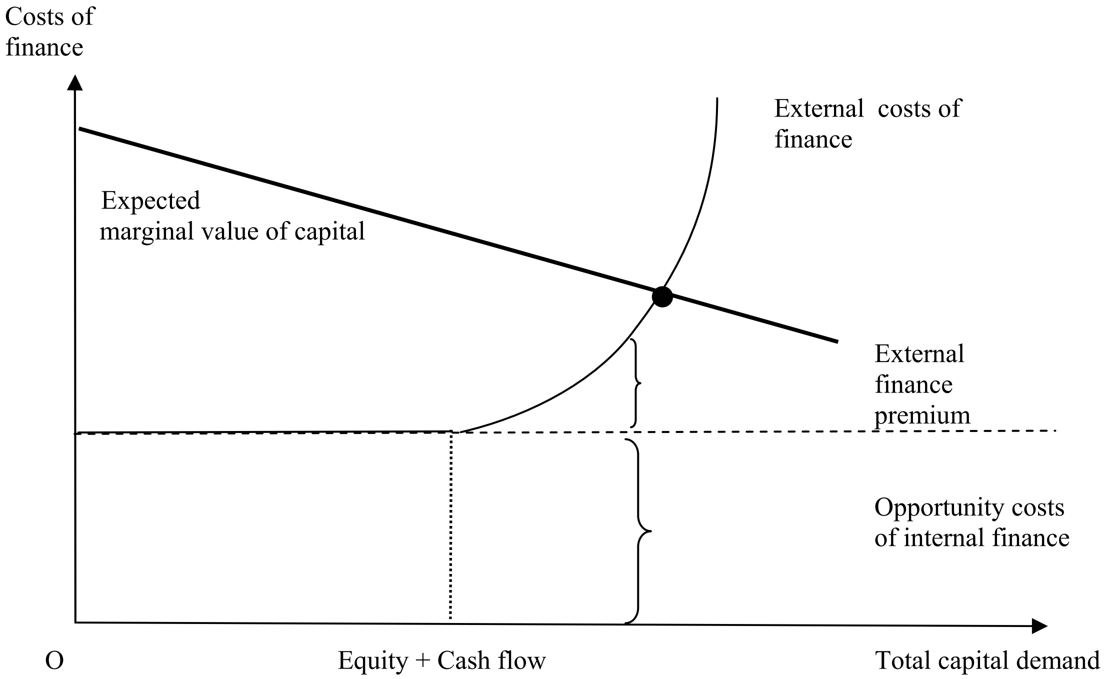

Figure 1, adapted from Bernanke, Gertler and Gilchrist (1999), illustrates that the costs of external finance depend on the difference between the actual capital demand and what can be financed internally. By means of this figure, we can interpret the responses to the questions on financial constraints in terms of three regimes which are ordered in a natural way: a state of no financial constraints, a state of limited internal finance (the firm needing external finance) and a state of unavailability of external finance. If a firm states that its capital expenditure authorisations are limited by a shortage of internal finance, it is saying that it has to pay an external finance premium because the internal resources are insufficient. And if it reports that no further external finance can be raised, the firm may find itself in the regime described by Stiglitz and Weiss (1981). In this case, the interest rate cannot be raised beyond a certain value, and the firm is credit-rationed. Under certain circumstances, this is the equilibrium outcome of a situation where the severity of the agency problems is a function of the interest rate itself. In Figure 1, the existence of such a regime would make the external costs of finance schedule break off at some maximum interest rate.

Consider an equation describing the capital accumulation decision, such as

$$I_{i,t}/\mathrm{K}_{i,t-1} = z_{i,t}'\beta + \gamma \mathrm{fc}_{\mathrm{i},t} + \varepsilon_{i,t}, \quad (1)$$

where $I_{i,t}/K_{i,t-1}$ is the investment rate, $z_{i,t}$ a vector of variables describing marginal profitability of investment, and $fc_{i,t}$ a variable describing external finance premia or quantitative constraints. The error term $\varepsilon_{i,t}$ will be correlated with the financial constraints variable via a second equation that explains the financial constraints indicators as a function of the financial structure and capital demand. The external finance premium will depend, among other things, on the inherited ratio of net debt to installed capital, $D_{i,t-1}/K_{i,t-1}$ and financing needs $I_{i,t}/K_{i,t-1}$:

$$fc_{i,t} = f(D_{i,t-1}/K_{i,t-1}, I_{i,t}/K_{i,t-1},...) + \eta_{i,t}. \quad (2)$$

This simultaneous relationship makes the predicted sign of γ in equation (1) indeterminate under the conditions of binding financial constraints.[2] If we had continuous variables describing the accumulation of capital, this problem could be resolved using instrumental variables techniques or GMM methods. Chapter 1 explores the informational content of German Ifo survey data using GMM estimators. Breitung, Chirinko and von Kalckreuth (2003) investigate the simultaneity of investment decisions and financial conditions by estimating a VAR on a large panel of German manufacturing firms.

[2] Let the external finance premium be a function of net debt to installed capital, $D_{i,t}/K_{i,t-1}$. With CF as cash flow and Div as dividend payment, the equation of motion for net debt is given by $D_{i,t} = D_{i,t-1} - CF_{i,t} + I_{i,t} + Div_{i,t}$. After solving for optimal dividend payment in terms of the predetermined variables, the equation for $fc_{i,t}$ assumes the general form (2). On the relationship between investment demand and balance sheet pressure, see Benito and Young (2007).

However, instrumental variable analysis is made difficult by the fact that the ITS data on investment and expansion are qualitative: we know whether or not the firm expands or steps up investment, but not by how much. Furthermore, there is no data on the financial structure in the ITS.

We therefore want to test the informational content of the data on financial constraints by looking at a relationship where both lines of causality point in the same direction. To this end, we investigate the occurrence and the duration of spells of capacity restrictions.

If there are adaptation costs such as delivery lags or time to build constraints, the move to a higher desired capital stock will be spread over several periods. Following Hayashi (1982), it is often assumed that marginal adaptation costs increase linearly with the size of investment. Given a certain predetermined level of indebtedness, $D_{i,t-1}/K_{i,t-1}$, the external finance premium will also be an increasing function of the planned rate of investment, prolonging adjustment further. The adjustment dynamics of financially constrained and unconstrained firms are likely to differ.

Chapter 1, building on a model by Schworm (1980), studies the investment dynamics following permanent productivity shocks. In the absence of adaptation costs, the unconstrained firm is able to adjust immediately, satisfying any financing needs at constant marginal costs. A financially constrained firm, however, faces marginal costs of finance that increase with the indebtedness ratio. Such a firm will realise only part of the adjustment immediately. The rest is spread over a certain time interval, financed by internal cash flow, which is also used to repair balance sheet ratios gradually. More generally, creditors may want to give finance in instalments, splitting the project into several phases, in order to monitor feasibility and the willingness of the management to comply with the terms of the credit contract. This may induce a sequential and 'evolutionary' development of a project from a smaller to a larger size even in cases where, in a world without information asymmetry, a massive parallel investment effort might have been optimal.

In the extreme case, when a firm has no access to external finance, the amount of investment per period is quite simply limited by the firm's cash flow. Under this assumption, Basu and Guariglia (2002) compare the reaction of financially constrained firms to transitory, serially uncorrelated productivity shocks. Again, the unconstrained firm can accommodate any shock fully within the same period. Therefore its optimal capital stock does not depend on the current realisation of the transitory shock, and marginal returns are uncorrelated for unconstrained firms. Constrained firms, when faced with adverse profitability shocks, may have to let their capital stock fall below equilibrium as they have only current cash flow to finance reinvestment and expansion. In such a situation, constrained firms must restore their capital stock gradually. During transition, marginal returns are high and autocorrelated. This – and the implication that unconstrained firms are able to react faster to common shocks, is the basis of Basu and Guariglia's tests on financial constraints.

The ITS survey gives us information on whether or not a firm experiences capacity restrictions by asking the following question:

Question 14: What factors are likely to limit your output over the next four months? *(please leave completely blank if you have no limits to output)*

orders or sales	skilled labour	other labour	plant capacity
credit or finance	materials or components	other	

Both directions of causation between financial constraints and the expansion decision lead us to predict that a state of capacity restrictions is more probable and will be of longer duration if the respondent also reports financial constraints to investment. If a firm reports capacity restrictions, this indicates a gap between the existing and the desired capital stock. Let us look first at the line of causation that runs from equation (2) to equation (1). A high $fc_{i,t}$ in equation (1) – induced by high indebtedness or a large financial shock $\eta_{i,t}$ – will make that the investment corresponding to a given $z_{i,t}$ is spread out over a longer period of time, inducing and prolonging capacity restrictions. On the other hand, with a given financial structure, a high realisation of $z_{i,t}$ or a large shock $\varepsilon_{i,t}$ in equation (1) will not only lead to capacity restrictions and a long adjustment process, but also trigger financial constraints in equation (2). Larger gaps take more time to fill, and this is reinforced when financial constraints are present. We can see that each of the two relationships alone is sufficient to explain a positive relationship between financial constraints and the frequency and duration of capacity restrictions.

3 The data set

The CBI Industrial Trends Survey (ITS) is a qualitative survey that looks at short and medium-term trends in the UK manufacturing and processing industries. It is a postal questionnaire aimed at a senior level within firms. The CBI produces both a monthly and quarterly survey, the latter providing more in-depth analysis. It covers a wide range of subject areas including optimism regarding the general and export business situation, investment, capacity, order books, numbers employed, output, deliveries, stocks, prices, constraints to output, export orders and on investment, competitiveness regarding domestic, EU and non-EU market, innovation and training. The quarterly survey is the empirical basis for our analysis. Mitchell, Smith and Weale (2002a and b) have used the ITS micro data to show that disaggregate survey based indicators they developed can outperform traditional aggregate indicators. The full text of the questionnaire can be found in Wood (2001).

According to the CBI, the ITS represents around 33% of the total current employment within UK manufacturing. The survey has an average response rate of 1,000, around 50% of the total number of firms that are on the survey panel. The survey has a core of around 800 companies, the rest being floating participants. The survey sample is constructed from a broad mix of CBI membership, trade association member companies and others, with the aim of ensuring both sector and regional representation.[3] Our investigation focuses on 11 years of data between January 1989 and October 1999. The cleaned, unbalanced panel contains 49,244 quarterly observations on 5,169 firms. We exclude any divisions of a company, as their information might not be truly relevant to questions relating to size or financial constraints. Furthermore, we exclude all anonymous responses because these companies cannot be tracked over time. For these reasons, our descriptive statistics are not identical to the results published by the CBI.

The survey consists of four employment size groups, the largest of which looks at small firms with fewer than 199 employees. As can be seen in Table 1, 63% of the ITS observations refer to these small firms. The CBI uses these data to produce a report entitled

[3] See Wood (2001), describing the current state of affairs. During our sample period the response rate was slightly higher. Our raw data include 51,381 observations from 44 quarters, ie 11,68 observations on average.

the Quarterly SME Trends Survey, one of the most comprehensive specialist surveys in the SME field. Table 2 shows the breakdown of two-digit SIC codes by observation.

In our raw data, respondents are grouped in four size categories: 0-199 employees, 200-499 employees, 500-4,999 employees, and 5,000 employees and more. In order to compare the experience and constraints of small and larger firms, we simplify the size categories further, classifying as 'small' those firms with fewer than 199 employees and as 'large' all those with 200 employees and more. Thus we are adopting the definition of a small firm used in the CBI's Quarterly SME Trends Survey. There are other common SME definitions. The DTI classifies firms with fewer than 250 employees as SMEs, whereas the European Commission and the Companies ACT use compound definitions, that combine a threshold of 250 employees with upper bounds for turnover and balance sheet total.[4] Given the nature of our size information, our categorisation is clearly the closest we can get to these other definitions. A lower employment threshold of 200 may arguably compensate for the lack of additional thresholds for balance sheet total and turnover. Using a higher cut-off value of 500 employees for the definition of an SME would severely diminish the number of large firms in our statistical tests. However, we made sure that our main conclusions stay intact using this alternative threshold.[5]

Tables 3 and 4 give the descriptive statistics related to the questions on constraints to investment and output. All figures within the respective size categories are simple, unweighted averages. Of the factors named by firms as likely to limit their output over the next four months (Survey Question 14), by far the most important was orders or sales, with over 80% of both small and large firms citing this particular factor (Table 3). Lack of skilled labour was a slightly more significant factor for small firms than for large firms. Credit and finance was mentioned rarely by both sets of firms, although small firms did show a higher propensity to cite this factor with a figure of 6% of small firms compared with 3% of large firms. Interestingly, plant capacity was clearly more impor-

4 According to the European Commission, a firm classifies as SME if it has fewer than 250 employees and either the turnover does not exceed € 40 million of the balance sheet total does not exceed € 27 million. In addition, an independence criterion regarding dominant ownership must be met. The UK Companies Act similarly qualifies a company as small or medium if it meets two of three of the following criteria: a maximum of 250 employees, a maximum of £11.2 million turnover and a balance sheet total not exceeding £5.6 million. For details, see Bank of England (2004), page ii.

5 Results by size classes and using an upper threshold of 500 for SMEs are available upon request.

tant to large firms: 17% of large firms saw their output constrained by capacity, whereas only 13% of small firms did. We will have a closer look at this relationship later on.

Turning now to obstacles for investment spending, Table 4 shows both the overall frequency with which firms cite a given constraint (any rank) to investment expenditure and the frequency with which this constraint was given the first rank. Firms could name more than one constraint on capital expenditure, but they were asked to rank the importance of their constraints. We interpret the answers to this question as information on marginal investment. For the entire sample, uncertainty about demand is the most common impediment mentioned by all firms. It is cited as the most significant constraint by 55% of all firms over the time period we studied. An interpretation of these figures in the light of theory, however, has to take into account the possibility that many firms focus only on 'downside risks', such as an unanticipated decrease in demand, rather than on uncertainty in the sense of imprecise expectations. For a recent review on the microeconometric literature on investment and uncertainty see von Kalckreuth (2003). The second most important constraint is inadequate net return, ranked by 39% of firms as their number one constraint. Other constraints seem to have been less important. Cost of finance was cited frequently in the early 1990s, but have been mentioned significantly less often since then.

Table 4 also breaks down the complete data set into small and large firms. These size classes show a number of differences in the importance given to the surveyed factors that could limit a firm's capital expenditure. Demand uncertainty seems to be a more important issue for smaller firms than it is for larger firms. This is not implausible: a firm which combines many imperfectly correlated activities will find its overall demand less volatile than a firm with a smaller number of activities. Furthermore, it is conceivable that small firms are used to meet peak demands in larger firms' order books and are cut out when orders fall. We also see that inadequate net return seems to bother large firms more than small firms.

Turning to financial issues, we see that 5.1% of small firms cite the inability to raise external finance as a factor likely to limit their capital expenditure over the next 12 months, but only 2.3% mentioned this particular factor as their foremost constraint. This compares with figures of 3.0% and 1.4% respectively in the case of large firms. Therefore, although this severest form of financial constraint is more prevalent amongst small firms, the proportion affected is very low. Overall, it was the constraint least commonly cited by small firms.

Small firms cite the shortage of internal finance less commonly than do large firms, with only 18.1% of small firms mentioning internal finance as a limiting factor compared with 20.2% of large firms. A finer breakdown (not shown) reveals that almost 30% of the firms in the largest size category, 5,000 employees and over, claim to be constrained by the shortage of internal finance. This is somewhat surprising, but it is conceivable that the pressure for high and regular dividends is felt especially strongly by the larger quoted companies. On the other hand, some small firms might find it easier to draw on the private wealth of their owners in the event of liquidity shortages. The cost of finance is a concern for both small and large firms, with a slightly higher proportion of small firms citing it as their main limiting factor.

For inferential purposes, it is important to know whether there is sizeable individual variation in the financing constraints data. Table 5 conditions on whether in the preceding period a firm reported either a shortage of internal finance or inability to raise external finance, and it shows the transition to the next period. It is easy to see that the reports on financial constraints are strongly autocorrelated. Among the firms that do not report financial constraints in a given period, 90.4% will continue to do so in the next period, with 9.6% switching to reporting constraints. But only 36.7% of the firms that report financial constraints in one period will state that they are unconstrained the next time; the remaining two-thirds will claim to be still constrained. However, the state of financial constraints is far from being determined by the state in the preceding period – there is lot of individual movement in both directions.

4 Investigating the link: financial constraints and capacity restrictions

This section compares the occurrence and duration of capacity restrictions for constrained and unconstrained financing, with an emphasis on the distinction between small and large firms.

4.1 Association analysis for capacity restrictions and financial constraints

Table 6 compares the frequency of capacity restrictions for three groups of firms: those that do not seem to be limited by the lack of either internal or external finance ("Not constrained"), those that complain about shortages of internal finance but not about the ability to raise external finance ("Internal finance") and, finally, those that report being rationed on the market for external finance ("External finance"). Whereas only 12.74% of the first group claims to be capacity-restricted, the corresponding figures are 20.74% of the second group and 20.06% of the third group. The two latter groups are clearly different from the first group. We perform three statistical tests of association: the well known Pearson test, a likelihood ratio test and Fisher's exact test, and all reject the null hypothesis of independence with a p-value of less than 0.0005.[6] The picture we can gather from comparing small and large firms in this respect (not shown) is essentially similar.

The association between the levels of the financial constraints and capacity restrictions might be the result of a special sensitivity to constraints in general on part of the individual respondents. To put it differently: some individuals might have a special propensity to complain. Therefore we want to condition on the state of capacity restrictions in the preceding period, thereby looking at changes of state. This examination also anticipates our duration analysis: by definition, a switch from an unrestricted to a restricted state initiates a spell of restricted capacity. If the restricted state is maintained, the spell goes on, and a reverse switch will end it.

Table 7 performs the three above-mentioned non-parametric association tests separately for firms that reported capacity restrictions in the preceding period and those that did not. Generally, capacity restrictions are cited much more frequently when there were the same sort of restrictions in the previous quarter: Whereas only 7.2% of the unrestricted firms switch to the restricted state, 53.3% of the restricted firms remain restricted. How-

[6] Given two discrete (multinomial) variables, all three tests focus on how strongly the realised shares for one variable, conditional on the values that the other variable may take, deviates from the overall shares. Pearson's test and the likelihood ratio test are easily calculated and rely on asymptotic properties of the test statistic: for large numbers their distribution converges against the Chi(2) with $(r\text{-}1)(s\text{-}1)$ degrees of freedom, r being the number of rows and s being the number of columns in the contingency tables. Fisher's test exploits the exact distribution of the test statistic, but computation can take a very long time for larger tables. See, for example, Büning and Trenkler (1994) or any other monograph on non-parametric statistics.

ever, under both conditions the probability of capacity restrictions clearly becomes higher when financial constraints are present. Again, the three association tests mentioned above reject the null hypothesis of independence with a p-value of less than 0.0005.

Tables 8 and 9 reveal an interesting difference between large and small firms. Among the firms that did not report capacity restrictions in the previous period, there is no clear size differential for transition rates. But among the restricted firms, a large firm will stay restricted with a probability of 57.8% (Table 9, lower half), whereas it is only 49.9% for small firms (Table 8, lower half). A closer inspection of the two tables shows that most of that difference is due to different conditional probabilities of capacity restrictions when there are no financial constraints. Transition probabilities of financially constrained large and small firms are similar. This might indicate that the duration of capacity restrictions is shorter for small firms. We also see that the transition rate is more affected by financial constraints when the firm is small: for large firms, the difference between financially constrained and unconstrained firms is less accentuated, albeit still significant.

4.2 The design of the duration analysis

We now proceed to consider the duration of states of restricted capacity. To the best of our knowledge, the duration of capacity restrictions has never been investigated before at a micro-econometric level. This makes our exercise interesting and worthwhile in its own right, as capacity restrictions may play an important role in the propagation of inflationary shocks.[7] For a firm in this state, the probability of switching to the unrestricted state may depend on the duration that is already achieved. Such a conditioning on time is called 'ageing', and the word itself makes the idea plain. Mortality among human beings is relatively high during the first months of life, dropping sharply after a couple of years. In advanced age, mortality rises again and reaches extreme levels at the right end of the scale.[8]

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7 See Álvarez-Lois (2004) and Macklem (1997).

8 The econometric analysis of duration data began only in the late 1970s; see Heckman and Singer (1984) and Kiefer (1988) for compact overviews. Not only the statistical models but also a good part of the terminology are borrowed from biostatistics. The classical focus of 'survival analysis' is the evaluation of survival times of human patients or animals after the contraction of a specific disease,

In order to estimate survival curves, we need to have information on the time when the period of constrained capacity began. We limit ourselves to contiguous strings of observations that start with a switch of the capacity restrictions variable from zero (no capacity restrictions reported) to one (output is likely to be limited by plant capacity during the next four months). The string is interrupted if either the state is left, i.e. the ‘spell’ ends, or there is no further information on the firm. One missing survey is enough to cut the string off. For inferential reasons, we can use only those observations which are not censored immediately after entry. That is, after the initial switch from zero to one, we need at least one more consecutive observation on the firm if the string is to contain any information on duration other than that it was non-negative. The cleaned CBI survey data for the period between January 1989 and November 1999 contain 49,244 observations on 5,169 firms. In this data set, we observe 1,431 of such strings, with a total of 5,153 observations, taken from 862 firms.[9]

We need to pay special attention to three important features of our data set. First, our duration data are censored considerably. From our 1,431 cases, we observe the end of the spell 1,210 times, but in the remaining 221 spells the string is cut off by missing observations. In these cases, we know that the spell has lasted at least until the end of the string, and this information has to be used appropriately. Second, we have grouped data. We do not observe the end of the spell in continuous time, but only know that it falls in an interval between two discrete points. Our observations are quarterly, and the vast majority of observed periods of capacity restrictions are less than four quarters. This means that the granularity of our observations is rather high, and we believe that it would not be correct to use standard models and estimation procedures which assume observed duration times to be continuously distributed in time. Third, as already stated, we are working with a panel of survival time data. For many firms, we observe more than one spell. These cannot be assumed to be stochastically independent, and special care has to be taken with testing procedures.

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with the aim of testing the effects of medical treatments and other factors that might potentially be of relevance.

9 This number of observations includes the initial zero and the initial 1 for each string.

4.3 Kaplan-Maier survival curves

We start by looking at the estimated survivor functions. A survivor function is defined both for discrete and continuous distributions by the probability that the duration *T* exceeds a value *t* in its range. For each hypothetical duration *t*, the survivor function gives the share of individuals with a duration of *t* or more. In our context, the survivor function depicts the process of firms liberating themselves from capacity restrictions, once they have entered into this state.

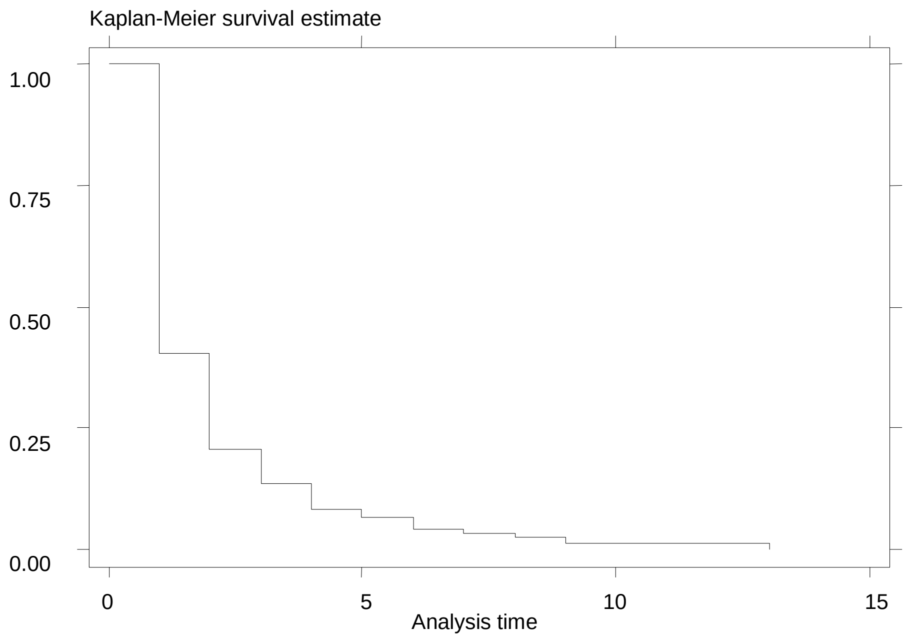
The Kaplan-Meier[10] estimator is a non-parametric maximum likelihood estimator of the survivor function. The starting point is an estimation of the conditional probability that an individual 'survives' in the state, given that it has endured until the last observed time to completion. The unconditional probability that the duration exceeds a certain value *t* is then computed as a product of the contemporaneous and all prior conditional survival probabilities. For this estimate to be unbiased, the censoring mechanism needs to be independent, that is, the completion probabilities of non-censored and censored individuals must be identical. This will be assumed throughout below.

Table 10 not only describes termination and censoring over time, but also gives the numerical values for the survivorship and completion rates in the entire sample. The first column, time, is the number of quarters after the original switch from unconstrained to constrained. If, for example, the capacity state of a firm switches from unrestricted to restricted in the third quarter of 1991, then for this firm the fourth quarter of 1991 assumes the value of 1. The second column gives the number of firms 'at risk', for which we have information in this duration interval. The third column gives the number of completions and the fourth column the number of firms censored in this quarter, on which there is no further information thereafter. The sixth column is the estimated Kaplan-Meier survivor function, based on the estimated hazard rates in the fifth column according to Equation (4). According to this estimate, about 40% of firms that start out with capacity restrictions remain in this state for more than one quarter, 20% for more than two quarters, etc. After the fifth quarter, the survivor function has dropped to 6.4%. The longest observed duration is completed after 13 quarters. During the first three quarters, completion probabilities seem to be falling, i.e. there is negative age depend-

[10] For the derivation of the Kaplan-Meier estimator as a maximum likelihood estimator, see the appendix.

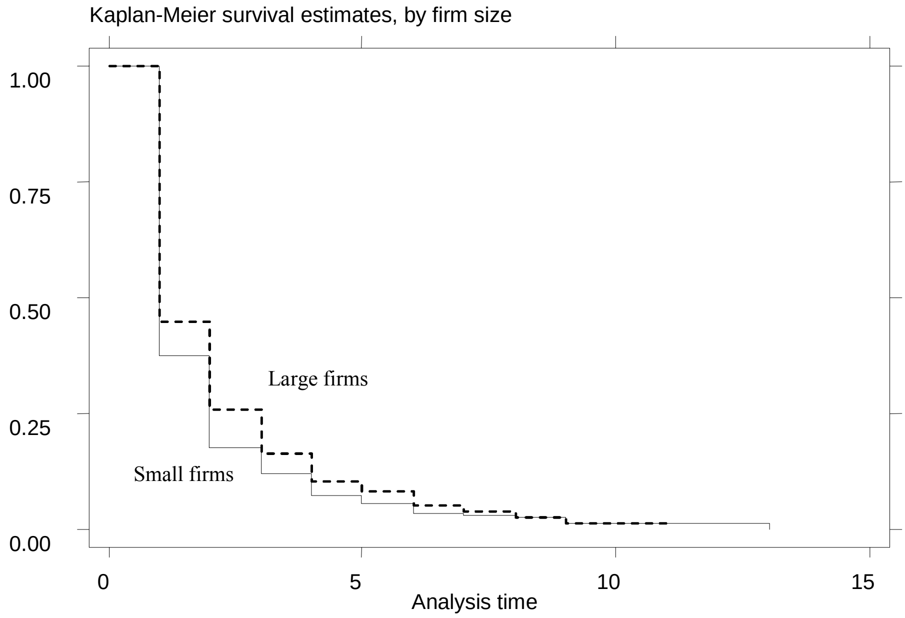
ence. The more time a firm has spent in a state of constrained capacity, the less likely it is to leave in the next quarter. From the fourth quarter on, the relationship ceases to be monotonic. The size of the sample on which duration information is based decreases rapidly with time. After the fifth quarter, not more than 3.7% of the original set of firms is left in the sample. It therefore seems inappropriate to draw any conclusions from survival times larger than that. The last column gives the standard deviation of the survivor function, taking into account the stochastic dependence of the duration experiences for a given firm. The standard deviations are simulated on the basis of a maximum likelihood estimation of the parameters using 20,000 replications. Numerically, they differ only very slightly from what is obtained assuming that all duration experiences are independent. The curve of the survival function given in Table 10 is plotted as Figure 2.

Figure 2: Kaplan-Meier estimates of the survival function for the entire sample



We want to compare the survivor experiences for various sub-samples. The relative sizes of the groups and some global statistics are given in Table 11. Figure 3 compares the duration experiences of small and large firms. Among the total number of capacity restrictions experiences, 887 were by small firms (with less than 200 employees) and 544 by large firms (200 employees and more). The survival curve of small firms is always beneath that of the larger firms. That is, large firms take longer than small firms to complete their spells of capacity restrictions.

Figure 3: Kaplan-Meier survival curves for small and for large firms



It is interesting to speculate on possible reasons. One explanation is that larger firms might be hit by disproportionately large demand shocks, ie shocks that are larger relative to their size. This does not seem immediately plausible; the law of large numbers should help to even out demand volatility for firms with larger and more diversified markets. However, it is conceivable that small firms cope with the volatility of market demand by tying themselves to larger firms and groups in exchange for an explicit or implicit insurance, thus smoothing their order book situation. Analogous strategies have been modelled to explain relationship banking in the context of firm finance, or implicit contracts in labour markets. Then, of course, it may also be the case that with their flat hierarchies and low co-ordination costs, small firms are more nimble and flexible in coping with demand shocks of a given size than the more bureaucratic large firms. A third potential reason for the slower response of large firms is external supply constraints in the machinery production industry. If one firm accounts for a large share of total demand for a certain specialised capital good, its rate of increase in capacity will be constrained by the capacity of the capital goods producers – inverting the accelerator principle. Presumably, large firms are in this situation more often.

Next we wish to look at survival experiences by financially constrained and unconstrained firms. The state is measured at the start of the spell. As before, there are two natural ways analytically to distinguish financially constrained and unconstrained firms. First, we can group a firm as financially constrained if it reports that it has to scale down investment because of insufficient internal funds. Second, we can classify it as financially constrained if it cites either shortages of internal finance or the inability to obtain external finance. The difference between the two groupings is in those 44 spells where firms cite the inability to obtain external finance as a limitation to investment, without indicating shortages of internal finance at the same time. As such a pattern is incompatible with either the standard pecking-order view of corporate finance under financial constraints or the natural ordering that results from costly monitoring models as shown in Figure 1, we prefer the less ambivalent first grouping.

Ultimately, 172 of the 1,431 spells start with the firm citing "cost of finance" as an impediment to investment. This answer might be considered a function of both the classical user cost of capital and the external finance premium. Among the 172 spells thus characterised, 64 cases are also characterised by lack of internal finance or inability to raise external finance. In the remaining 108 cases, cost of finance is named as an impediment without either lack of internal finance or the inability to obtain external finance being cited. Whereas the former configuration is consistent with a firm that has run out of internal finance and now faces a high external finance premium, the latter group seems to indicate high opportunity costs. Internal funds are available, but there is a higher yield for some alternative use. The 'cost of finance' was cited widely during the period of high interest rates at the beginning of the 1990s but has since become virtually negligible. According to the classical user cost mechanism,[11] opportunity costs are important for determining the 'desired' capital stock and thus whether or not there is net investment demand, given the current capital stock inherited from the previous period. This gap is controlled for by conditioning on firms that state capacity restrictions. What we are interested in, however, is whether financially constrained firms reach their

[11] See, among others, Jorgenson (1963), Hall and Jorgenson (1967), and Eisner and Nadiri (1968).

target later. We will therefore not use 'cost of finance' as an indicator of financial constraints in the body of our analysis. Lack of internal finance as a sorting criterion will qualify as constrained the 64 cases that are consistent with an interpretation in terms of an elevated external finance premium, but not the remaining 108 spells. However, towards the end of this section we give additional estimation results on the basis of a 'cost of finance' classification.

Figure 4: Kaplan-Meier survival curves for financial constrained and unconstrained firms

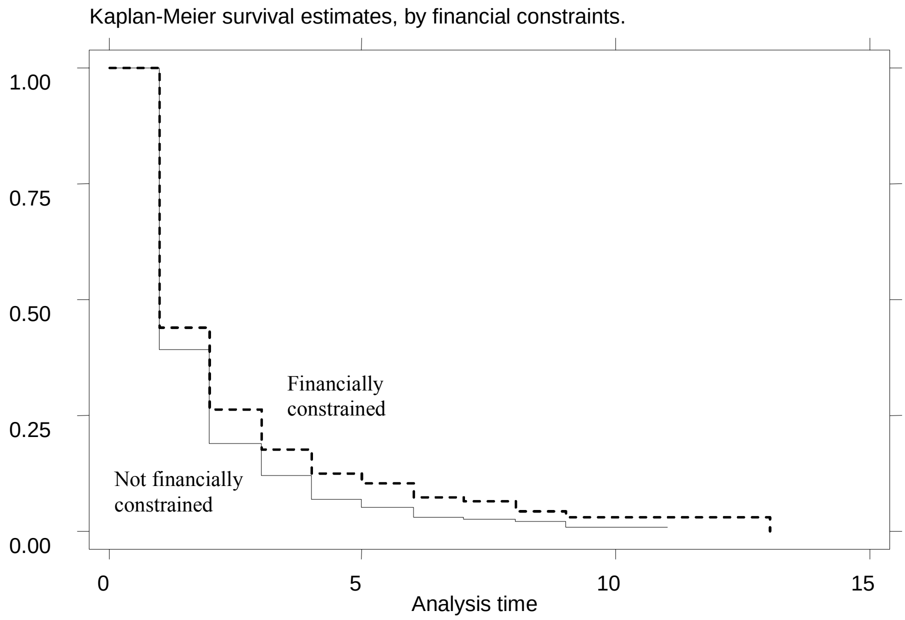


Figure 4 depicts the results for the first criterion (shortage of internal finance) for the whole sample. The survival curve for financially unconstrained firms is everywhere beneath the curve for the financially constrained firms. This means the unconstrained firms are able to complete their spell of restricted capacity faster than the constrained firms. It is convenient to point out again that there are two competing causal explanations for this difference. For a given size of the capacity gap, financial constrained firms might take longer to fill it. On the other hand, firms with a larger capacity gap (and accordingly higher financing needs) might be more likely to report financial constraints. Comparing the survival curves is essentially a test on whether at least one of these hypotheses is true.

Figure 5: Small firms only – Kaplan-Meier survival curves for financially constrained and unconstrained firms

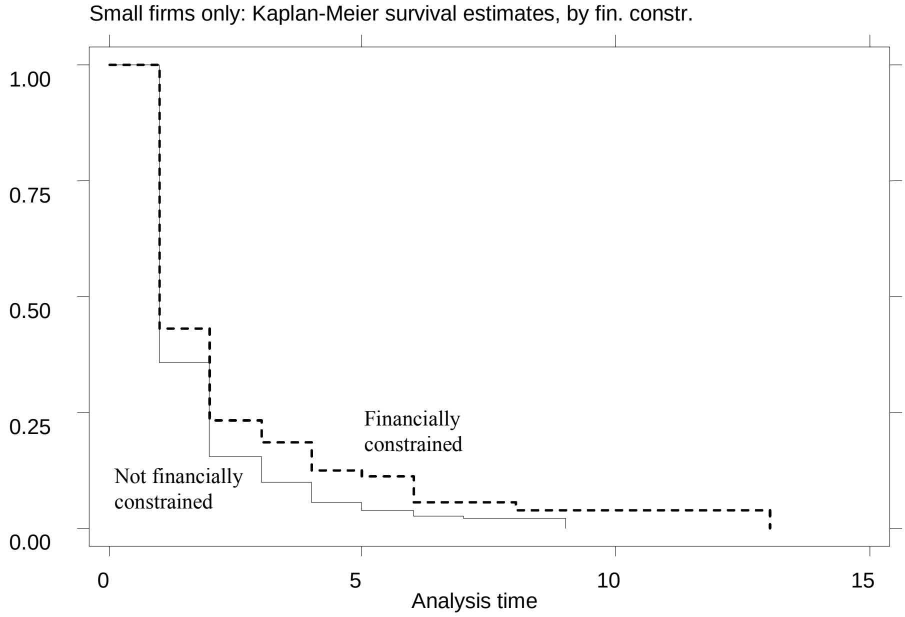
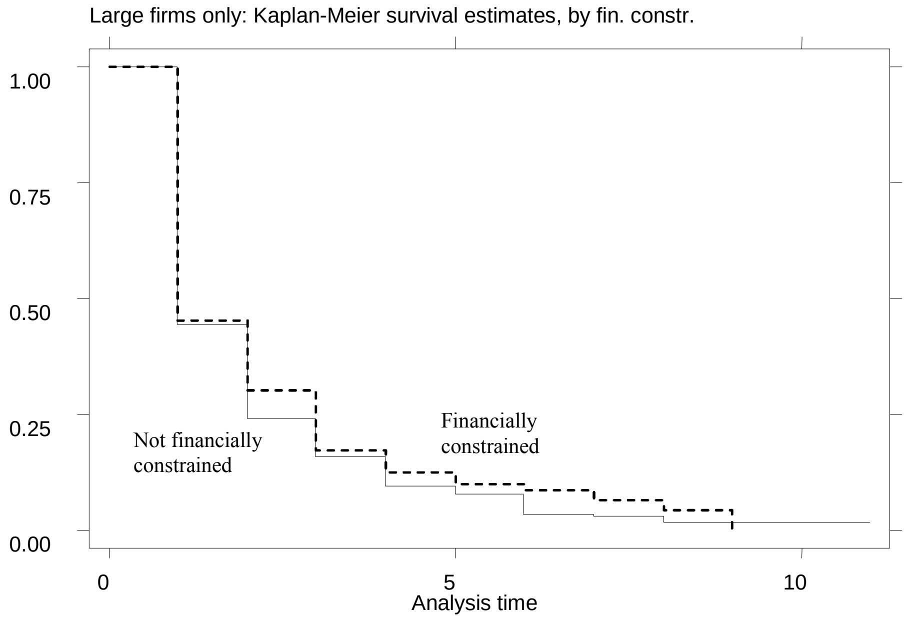


Figure 6: Large firms only – Kaplan-Meier survival curves for financially constrained and unconstrained firms



4.4 A proportional hazard (Cox) model of duration

It is instructive to look at the effect of financial constraints separately for small and for large firms. Figure 5 shows constrained and unconstrained small firms, and Figure 6 performs the same comparison for large firms. For both sub-samples, the curve for constrained firms is situated above the curve for unconstrained firms, as is expected. The graphs for the second criterion look essentially similar. Eyeballing suggests that the difference is more marked for small firms. It will be necessary to examine this and other differences statistically.

In order to test the effect of size and financial constraints on the duration of capacity restrictions, we need to impose some structure. Let $x=(x_1,x_2)$ be a two-dimensional vector of indicator variables for size and financial constraints. Specifically, $x_1=1$ indicates large size, and $x_2=1$ a state of financial constraints at the beginning of the spell. As we have little a priori information about the underlying process, we do not want to restrict the form of the baseline survival function that corresponds to $x=(0,0)$, the case of a small firm without financial constraints. In the following, we explicitly recognise (1) that duration is distributed continuously over time, and (2) the measurement of the capacity restrictions for a given unit is taken at discrete interval (quarters), *j = 1, 2, ... k*.[12] Let $\lambda(t,x_i)$ be the hazard for a unit with characteristics x_i at time t, defined as

$$\lambda(t,x)=\lim_{h\to 0} P\left(t\le T<t+h \middle|\ T\ge t,x_i\right)\Big/h\,. \tag{3}$$

The hazard is the instantaneous rate at which spells are completed by units that have lasted until time t, defined in the same way as a mortality rate in demographics or a failure rate in the statistical theory of capital stock dynamics. We want to assume that the characteristics x_i relate to the hazard rate in a proportional fashion:

$$\lambda(t,x)=\lambda_0(t)\cdot\exp(x_i'\beta)\ , \tag{4}$$

[12] The assumption of absolutely continuous time is made only for expositional convenience. A discrete time concept would not invalidate any of our results, after we have redefined the hazard rate in t as the conditional probability that the spell is completed in *t*+1, conditional on it having lasted until *t*. It is possible to conduct duration analysis with distributions of *T* that have both discrete and continuous portions. See Kalbfleisch and Prentice (2002) for a systematic approach.

with β being a vector of coefficients that needs to be estimated. The hazard ratio between an individual with characteristics x_i and the baseline case is given by $\exp(x_i'\beta)$, which is approximately $1+\beta$ for small values of β. The hazard ratios between two individuals with characteristics x_1 and x_0 are calculated as $\exp[(x_1 - x_0)\beta]$. Equation (4) constitutes the model of proportional hazard developed by Cox (1972). In this set-up, the baseline hazard remains completely unspecified, which is why the proportional hazard model figures among the semi-parametric approaches.

We assume that the spells of different firms are independent events and that the censoring mechanism is independent of the state of the firm. We can write the probability for the completion of a spell to be registered after *j* survey waves as a product of conditional probabilities. This allows us to derive a likelihood function that contains β as well as further (incidental) parameters describing, for the baseline case, the conditional probability of completing in the time interval between $j-1$ and j, given that $j-1$ has been reached.[13] The likelihood function can be shown to be identical to the likelihood function for a Bernoulli experiment with probabilities that depend on time as well as on x_i by means of a standard link function, the complementary log-log function. The parameter estimates are asymptotically normally distributed. The panel nature of the data is taken into account by computing robust standard errors, with clusters defined by the firm identity.

Table 12 contains the Maximum Likelihood estimations for a Cox model with two covariates: size and an indicator variable for the presence of financial constraints. As explained above, we use two alternative definitions of financial constraints. The dummy variable *fin(1)* takes a value of 1 to indicate that the firm cites insufficient internal finance at the outset of the spell. The dummy variable *fin(2)* will be 1 if the firm cites either insufficient internal finance or the inability to raise external finance. The respective classification is maintained during the entire spell.

In each cell, the first figure gives the estimated coefficients. Below, in curly brackets, this value is translated into a hazard ratio. Column (1), for example, compares the hazard rates for small and large firms. The hazard rate of a large firm is exp(–0.183) times the hazard ratio of a small firm, meaning that large firms are leaving the state of restricted capacity at a rate which is only about 83.3% that of a small firm. The third figure, in round brackets, indicates the robust standard deviations, taking into account stochastic dependence between spells generated by the same firm. Investigating the table, we see that the lack of internal finance lowers the hazard rate to approximately the same extent as large size: the hazard rate for a constrained firm is only 82.6% of an unconstrained firm, meaning a longer duration of the restriction experience. This remains true if we consider both characteristics at the same time. In Column (4), we introduce an interaction term, thereby allowing the sensitivity of large firms with respect to financial constraints to be different from that of small firms. In this regression, we can compare constrained small firms with unconstrained small firms using the *fin(1)* coefficient. Its value is 0.260, which is equivalent to a hazard ratio of 0.771. The hazard ratio of a large constrained firm (as opposed to a large unconstrained firm) is given by the sum of the *fin(1)* coefficient and the coefficient of the interaction term. We see that this coefficient is smaller, the estimated hazard ratio for large firms is only exp(–0.260+0.170) = 0.915. Furthermore, this value is not significantly different from zero. Performing a Wald test on whether the sum of the coefficients on *fin(1)* and the interaction term is zero, we obtain a value of the $\chi^2(1)$-statistic of 0.58, which is equivalent to a p-value of just 0.45. However, the difference in the sensitivity between small and large firms, given by the coefficient of the interaction term, is itself not significant. The last three columns of Table 12 give us the corresponding estimates with respect to our second indicator of financial constraints, *fin(2)*. The picture is essentially similar, although the measured difference in the sensitivity between small and large firms is somewhat smaller.

It may be argued that the detected differences between small and large firms may be sector-specific. As firm size (and possibly financial constraints) may be sector-specific too, we want to control for sectoral differences in order to avoid a missing variable bias. Table 13 repeats the estimates explained above, adding 20 dummies for 2-digit SIC sectors. This leads to a slight reduction in size effect: the hazard ratio goes up from 0.833 to 0.855. In the estimation featuring a size dummy, the *fin(1)* dummy and the

[13] The appendix contains the full details and a derivation.

interaction term, large size will lower the hazard rate by about 19%, lack of internal finance will depress it by almost 25%, but the interaction term, although still insignificant by itself, will neutralise almost the entire effect of financial constraints for large firms. Again, the estimates using the second criterion for financial constraints are very similar, although the measured effects seem less strong.

A third set of estimates, collected in Table 14, controls for the position in the business cycle, by including dummies for the time of the start of the spell. This is done in order to account for a possible dependence of duration on the general state of the economy. In a time of depression, investors might be less inclined to close capacity gaps. At the same time, internal financial resources might be scarcer and external finance might be more difficult to obtain. In our estimates, adding the controls for the business cycle situation makes the size effects come out more clearly, whereas the measured effects of financial constraints are somewhat smaller, as predicted. In our preferred estimate, which includes an interaction term, both characteristics lower the hazard rate by about 22% with respect to the baseline case. These two values are highly significant. For large firms, the interaction term lowers the financial constraints sensitivity by about one half. The hazard rate of a constrained large firm versus an unconstrained firm is measured at 91.6. Statistically, this is not significant – the $\chi^2(1)$-statistic yields a value of 0.94, corresponding to a p-value of 0.33.

Additionally, we have run an estimation that classifies a spell as financially constrained not only if a firm reports either lack of internal finance or the inability to obtain external finance, but also if 'cost of finance' is cited as an impediment to more investment. The use of time dummies in the current estimation context allows at least a partial neutralisation of the strong cyclical dependence of the 'cost of finance' statements. Using this indicator, *fin(3)*, financial constraints are no longer significant at the 5% level. For a model with financial constraints only, analogous to column (5) in Table 14, we obtain a coefficient of –0.12 with a z-value of 1.88 (p=0.060). Taking into account both financial constraints and size, as in column (6) of Table 14, the coefficient is –0.12, with a z-value of –1.92 (p=0.055). Adding an interaction term, as in column (7) of Table 14 we estimate a *fin(3)* coefficient of –0.14, with a z-value of –1.72 (p=0.085). We do not think, however, that *fin(3)* is an adequate indicator of financial constraints. As discussed earlier, the difference between *fin(2)* and *fin(3)* is given by those firms that report cost of finance as impediment to investment without reporting a shortage of internal finance or the inability to obtain external finance at the same time. This pattern is consistent with firms that have a more profitable alternative use for their internal resources, such as paying back debt. In this case, the classical user cost mechanism predicts a decrease of the desired capital stock. Thus there is no reason to expect that the spell of restricted capacity, indicating a difference between desired and installed capacity, will be very long for those firms.

The estimates for large and for small firms in Table 12, 13 and 14 are not independent, as the coefficients on the duration time dummies are restricted to be identical.[14] We want to repeat the comparison by estimating a proportional hazards model separately for large and for small firms. This is equivalent to including interaction terms for time dummies in the previous regressions. As we want to economise on degrees of freedom, we perform this regression only for the basic model without additional dummies indicating sector or date of spell origin. The results, collected in Table 15, do not differ perceptibly from what has been seen before: with small firms, the presence of financial constraints leads us to predict a smaller hazard and a longer duration of the capacity restrictions experience. For large firms, the estimated difference points in the same direction, but it is smaller and not significantly different from zero.

The size of the sample for our duration analysis is affected by the fact that we need to observe the start of the spell in order to take proper account of ageing. What if ageing is absent or unimportant, the hazard function memoryless? We could make use of all the strings that contain capacity restrictions and at least one further observation. And a look on Table 10 does not make the assumption of a constant completion rate look too harsh.

As a matter of fact, this brings us back to the association analysis given in Tables 7, 8 and 9. The lower halves of these tables look at the frequency of restricted and non-restricted capacity, given capacity restrictions in the previous period, separately for firms that do report financial constraints and those that do not. Under the assumptions made above, these are estimates of the conditional transition probabilities, and the distribution of the duration of spells would simply be geometric. And the three tests we have per-

[14] The time dummies are related to the conditional probabilities of completing for the baseline group.

formed are precisely the way to tell whether those transition probabilities are different. For both types of firms, financial constraints prove to be significant for the transition to the unconstrained state, but the difference between the estimated conditional probabilities effect was clearly lower for the large firms.

As a whole, our Cox regressions give us two statistically significant results and a consistent overall pattern. Holding everything else constant, size clearly has an effect on the duration of capacity restrictions. Hazard rates for large firms are about 20%-25% lower compared to small firms. Second, for small firms at least, financial constraints according to either of our two definitions make a difference. For a constrained small firm, the hazard is between 24% and 29% smaller than for an unconstrained small firm. For large firms, we do not find a statistically significant difference between constrained and unconstrained firms. We do not think that it is justified to conclude that financial constraints are unimportant or uninformative for larger firms. The results from the association analysis do not support this interpretation. It is quite possible that our sample size is not big enough to deliver significant results for our sub-sample of larger firms. The sensitivity difference between the two groups is insignificant everywhere. However, the overall pattern of a lower, but still positive dependence of duration on financial constraints is suggestive.

There are various possible interpretations for this “difference in differences”. First, standard theory suggests that financial constraints might mean less of a restriction for larger firms, especially when those are given by “lack of internal finance”. It may be easier and cheaper for them to obtain external finance, not only from banks and shareholders, but also from suppliers, in the form of trade credit. Furthermore, they might find it easier to absorb a given increase in financing costs by adapting other real activities, e.g. by decumulating inventories (when they are sure to enjoy priority status regarding supply), postponing hiring, scaling down training, or turning to renting and leasing capital goods. Finally, the costs of not being able to satisfy demand for an extended time can be considerable for a large monopolist who needs to deter potential competitors from market entry, as compared to small firms for which the perfect competition paradigm will often be better suited.

5 Conclusion and Outlook

In our study, we have focused on two questions. First, we looked at the interactions between financial constraints, defined as a shortage of internal finance or the inability to raise external finance, and capacity restrictions, signalling a gap between the actual and desired capital stock. Our association and duration analysis shows that the theoretical predictions are borne out empirically – as expected, financially constrained firms are more often capacity-restricted and take longer to close capacity gaps than unconstrained firms. This important result indicates that financial constraints and real activity are indeed interrelated. Alternatively, it constitutes an indirect validation of the survey responses on financial constraints.[15] They relate to other information in the data set in a way that is consistent with theory. Survey information on the ups and downs of financial constraints indicators can therefore be a potentially valuable policy tool.

Second, we use the data set to compare the importance of financial constraints for small and large firms. The CBI data set offers a unique opportunity for such comparisons, given the dearth of reliable micro data on small firms. Quantitatively, the differences between financially constrained and unconstrained firms are clear, but not large: a financially constrained firm will leave the state of capacity restrictions at a rate that is about 20% lower than for a firm that does not report financial constraints.

Concerning the importance of financial constraints for small and large firms, the descriptive statistics – somewhat surprisingly – do not show any clear distinction. For small firms, however, financial constraints make a clear difference: shortage of internal finance or the inability to raise external finance significantly prolong their spells of capacity restrictions. For larger firms, the measured effect is positive, too, but insignificant. As the association analysis has shown statistically significant differences between financially constrained and unconstrained large firms, we conclude that the relationship between financial constraints and the speed of adjustment is weaker for larger firms, but not absent. A finer breakdown (not presented, but see fn. 5) reveals that the effect of financial constraints on the completion rate decreases gradually by size. If we condition on firms reporting capacity constraints in the previous period, the effects measured by

[15] Plato's allegory of the cave teaches us that these two aspects of confronting theory with the data can never be fully separated.

association analysis turn insignificant for the two largest size categories. This result provides some justification for the practice of splitting samples according to size categories when investigating the effects of financial constraints.

Interestingly, large firms are capacity constrained more often. The analysis of association shows that this is due to financially unconstrained small firms with capacity restrictions leaving this state quicker than comparable large firms. Our formal duration analysis confirms this interpretation: small firms are able to close their capacity gaps faster.

Thus large and small firms do differ in the way they cope with their constraints, but these differences are more subtle than we had expected. The interesting pattern we found – small firms adapting faster in general, but with a speed that is more closely related to financial conditions – might be the basis for further theoretical and empirical work on comparative advantages of firms belonging to different size classes: we should expect to find small firms in sectors where there is a premium for rapid adjustment. And they can be at a relative disadvantage in areas with large peaks in the demand for finance or discontinuous cash flows, e.g. because of long gestation lags.

The precise nature of the relationship between the real and the financial spheres remains to be worked out. The measured differences between firms that report financial constraints and those that do not will partly be due to the effects that investment has on the firms' balance sheets. Real investment decisions may certainly cause financial constraints which slows down or prevent further expansion. Further research aims at identifying the two directions of causation using a structural approach.

Appendix: A maximum likelihood estimator for the proportional hazard model with censored grouped panel data

As has already been discussed, a very important feature of our data-set is that the observations are *grouped*. The observational units are surveyed in certain intervals and if there is a status change, we get to know only the left and the right boundary for the date when the change took place. And as the typical duration experience (spell) only lasts a few quarters, we have to take this limitation very seriously.

This makes it impossible to use many of the standard procedures that assume a continuous flow of information. In a certain sense, however, the restriction also makes life easier. As we do not see what happens in between two surveys, all survivor functions that yield the same pattern of probability masses on the intervals are observationally equivalent. It is only this pattern that counts for inferential purposes. And as there are not too many quarters, the pattern can be parameterised relatively easily.

Below, we think of the duration as distributed in continuous time. Information, however, arrives at discrete points and is supposed to cover the interval between two observations. Our derivation of a maximum likelihood estimator for the case of grouped data relies heavily on Hosmer and Lemeshow (1999), Sect. 7.4 (but also see Kalbfleisch and Prentice (2002), Sect. 5.8 for a more general exposition).

In Equation (3), the hazard function has been defined as the instantaneous rate at which spells are completed by units that have lasted until time t, just like a mortality rate in demographic analysis. Let $f(t,x)$ be the (continuous) density of duration *t* and $S(t,x)$ the survivor function, indicating the probability of duration of at least *t*, being the probability mass on the right tail of the distribution. Then the hazard function may be written as

$$\lambda(t,x) = \frac{f(t,x)}{S(t,x)} = \frac{d}{dt}\log S(t,x) \ . \qquad \text{(A.1)}$$

The hazard function completely determines the distribution. In survival analysis, the most widely used model to analyse the influence of covariates *x* is the proportional hazard model introduced into the literature by Cox (1972). Given a set of covariates and a vector of parameters β, the constituting assumption is

$$\lambda(t,x) = \lambda_0(t) \cdot \exp(x'\beta) \ . \qquad \text{(A.2)}$$

The hazard function for an individual with covariates x differs from a baseline hazard λ_0 by a multiple $\exp(x'\beta)$ that may or may not be constant. Most importantly for estimation purposes, the baseline hazard remains completely unspecified. Therefore, the Cox model is classified as a semi-parametric approach. The substantive content of the Cox assumption rests in the *hazard ratio* for two units with covariates x_0 and x_1:

$$\frac{\lambda(t,x_1)}{\lambda(t,x_0)} = \exp((x_1 - x_0)\beta) \ . \tag{A.3}$$

We want to develop a maximum likelihood procedure for the estimation of a proportional hazard model with censored grouped panel data. In our set-up, measurement is taken at certain intervals: $j = \{1,2,\ldots,k\}$. For all individual spells i, we define a censoring variable c_i that takes the value $c_i = 1$ if the end of the duration is observed, and $c_i = 0$ if not. Let $t = l_i$ be the time when the spell i is last observed. Calculating the probability of a given duration experience, we have to distinguish two cases. If $c_i = 1$ (not censored), we know that the duration was completed by $t = l_i$, and the completion event must have occurred somewhere in the interval between $l_i - 1$ and l_i. That means:

$$P_i = S(l_i - 1, x_i, \beta) - S(l_i, x_i, \beta) \quad \text{for} \quad c_i = 1 \ . \tag{A.4}$$

If $c_i = 0$, right censoring occurs in $t = l_i$. Up to the last observation, the event has not occurred, and the probability for this outcome is:

$$P_i = S(l_i, x_i, \beta) \ . \tag{A.5}$$

This fundamental distinction is typical for estimation with censored data; see, for example, Maddala (1983), Chapter 6, or Wooldridge (2002), Chapters 16 and 20. Assuming for a moment that the spells are independent, we may write the likelihood function as

$$\begin{aligned} L &= \prod_{i=1}^{n} \left\{ S(l_i, x, \beta)^{1-c_i} \cdot \left[S(l_i - 1, x_i, \beta) - S(l_i, x_i, \beta) \right] \right\} \\ &= \prod_{i=1}^{n} S(l_i - 1, x, \beta) \left\{ \left(\frac{S(l_i, x_i, \beta)}{S(l_i - 1, x_i, \beta)} \right)^{1-c_i} \cdot \left(\frac{S(l_i - 1, x_i, \beta) - S(l_i, x_i, \beta)}{S(l_i - 1, x_i, \beta)} \right)^{c_i} \right\} \end{aligned} \tag{A.6}$$

The seemingly unwieldy transformation above yields a key insight. Both the censored and the uncensored individuals contribute the amount $S(l_i - 1, x, \beta)$ to the likelihood, the information that the duration of the experience had not ended by $l_i - 1$. *Conditional on this information*, the contributions differ only for period $t = l_i$. For the non-censored durations with $c_i = 1$, the spell has ended by $t = l_i$. This event has the conditional probability

$$\theta_{i,j} = \frac{S(j-1, x_i, \beta) - S(j, x_i, \beta)}{S(j-1, x_i, \beta)} \quad \text{for } j = l_i . \tag{A.7}$$

The above expression is the probability that completion takes place between $l_i - 1$ and l_i, given the fact that it has already lasted until $l_i - 1$.[16] For the censored cases, we have the information that the spell has not ended in $t = l_i$, the conditional probability of which is

$$(1 - \theta_{i,j}) = \frac{S(j, x_i, \beta)}{S(j-1, x_i, \beta)} \qquad \text{for } j = l_i . \tag{A.8}$$

Lastly, we may rewrite the survivor function in $t = l_i - 1$ as the product of conditional survival probabilities for all periods up to $l_i - 1$:

$$S(l_i - 1, x, \beta) = \prod_{i=1}^{l_i - 1} (1 - \theta_{i,j}) . \tag{A.9}$$

Substituting these expressions into (A6) yields the likelihood function:

$$L = \prod_{i=1}^{n} \prod_{j=1}^{l_i - 1} (1 - \theta_{i,j}) \cdot \left(\theta_{i,l_i}{}^{c_i} + (1 - \theta_{i,l_i})^{1-c_i} \right) . \tag{A.10}$$

We can rewrite this expression in a way that permits the maximum likelihood estimation using standard software. For each spell *i*, and for all $t \le l_i$, we define the artificial outcome

$$z_{i,t} = \begin{cases} 1 & \text{if } c_i = 1 \text{ and } t = l_i \\ 0 & \text{else} \end{cases} . \tag{A.11}$$

Using this variable in (A10) yields an expression that has the form of the likelihood for a generalised binary regression model:

$$L = \prod_{i=1}^{n} \prod_{j=1}^{l_i} (1 - \theta_{i,j})^{1 - z_{i,j}} \cdot \theta_{i,j}{}^{z_{i,j}} . \tag{A.12}$$

[16] This conditional probability of completion is conceptually similar, although not identical, to the hazard rate defined above in equation (A.1). However, whereas $\theta_{i,j}$ is a true probability that is defined over an interval, the latter is an instantaneous rate that refers to a single point in the distribution and is allowed to have values greater than one. This is analogous to the relationship between a density of a continuous random variable and the probability that a value in a certain interval is assumed.

For each duration experience *i*, (A.12) is the likelihood for l_i independent binary observations with probabilities $\theta_{i,j}$ and outcomes $z_{i,j}$. In order to use this for an estimate of β, we need the link function that relates $\theta_{i,j}$ to the covariates x_i. A link function is a transformation such that the transformed probability $\theta_{i,j}$ is a linear function of x_i. With some algebra, we can show that under the Cox assumption (A.2), the following relationship holds for the survivor function:

$$S(t,x,\beta) = S_o(t)^{\exp(x'\beta)} \quad , \tag{A.13}$$

and some more algebra yields the following link function:

$$\ln[-\ln(1-\theta_{i,j})] = x'\beta + \tau_j, \qquad \text{where} \tag{A.14}$$

$$\tau_j = \ln\left[-\ln\left(\frac{S_0(j)}{S_0(j-1)}\right)\right] . \tag{A.15}$$

The link function (A.14) is the complementary log-log function. After creating artificial values *j* and $z_{i,j}$ for each interval $t \le l_i$, we define time dummies for each interval *j*. We can estimate β and the τ_j as the coefficients of the covariates and the time dummies, respectively, using a binary regression package with the link function (A.14).[17]

Several firms contribute more than one duration experience. We take account of the panel nature of our data-set calculating robust standard deviations clustered with respect to the firm, rather than those standard deviations that assume independence. This allows for an arbitrary correlation pattern for the observations of any given firm. The assumption of independence between firms, however, is retained.

By means of (A.15), we can recover the maximum likelihood estimates of the baseline conditional survival probabilities, $S_0(t)/S_0(t-1)$, taking into account the fact that $S_0(0) \equiv 1$. Calculating their products yields the estimate of the baseline survivor function. In a model without covariates, the survivorship function estimated in this way is identical to the Kaplan-Meier estimator discussed earlier. The standard deviations in Table 10 were calculated by simulating survival curves with 20,000 replications of $\tau_j, j = 1,...,8$, on the basis of the maximum likelihood estimation of the parameter and the variance-covariance matrix. In the presence of covariates x_j, the baseline survivorship function refers to a hypothetical unit with covariates $x_j = 0$. This is easy to inter-

[17] For our estimations, we used the cloglog routine in Stata, version 8.

pret if the covariate is an indicator variable for a sample split. In more complex cases, however, the baseline survivor function does not necessarily make sense by itself.

Table 1: Breakdown of data set by employment size

	Employment Size				
	1 – 199	200 – 499	500 – 4,999	5,000 and over	Total
No. of firms	3,394	1,060	647	68	5,169
No. of obs.	31,089	10,222	6,994	939	49,244

Table 2: Number of observations, by employment size and 2-digit SIC code

2-Digit SIC code	Employment Size				
	1 – 199	200 – 499	500 – 4,999	5,000 and over	Total
Coke ovens	17	6	17	0	40
Mineral oil processing	73	35	38	11	157
Nuclear fuel production	0	0	0	2	2
Extraction and preparation of metalliferous ores	35	0	0	0	35
Metal manufacturing	1,429	460	292	62	2,243
Extraction of minerals not elsewhere specified	493	60	103	9	665
Manufacturing of non-metallic mineral products	1,286	436	443	85	2,250
Chemical industries	1,191	722	641	79	2,633
Production of man-made fibres	142	8	32	1	183
Manufacturing of metal goods not elsewhere specified	3,048	651	308	6	4,013
Mechanical engineering	7,116	1,718	1,028	23	9,885
Manufacturing of office machinery and data processing	103	26	90	7	226
Electrical and electronic engineering	2,991	1,420	808	54	5,273
Manufacturing of motor vehicles and parts thereof	691	409	409	187	1,696
Manufacturing of other transport equipment	315	132	136	111	694
Instrument engineering	838	230	69	0	1,137
Food, drink and tobacco manufacturing industries	1,162	649	874	194	2,879
Textile industries	2,427	1,098	594	7	4,126
Manufacturing of leather and leather goods	295	63	2	0	360
Footwear and clothing industries	1,439	478	262	39	2,218
Timber and wooden furniture industries	1,258	313	154	1	1,726
Manufacturing of paper and paper products	2,854	668	489	38	4,049
Processing of rubber and plastics	1,698	563	169	22	2,452
Other manufacturing industries	188	77	36	1	302
Total	31,089	10,222	6,994	939	49,244

Table 3: Small and large firms' output restrictions

		Orders or sales	Skilled labour	Other labour	Plant capacity	Credit or finance	Materials or components	Other
Small Firms	Any rank	82.74%	13.74%	2.76%	13.03%	5.60%	4.83%	1.34%
(empl < 200)	Rank 1	80.39%	7.96%	1.28%	8.84%	2.57%	2.34%	1.05%
Large Firms	Any rank	80.15%	11.80%	2.26%	16.74%	2.77%	5.64%	1.89%
(empl ≥ 200)	Rank 1	77.65%	7.14%	1.17%	11.73%	1.05%	3.02%	1.60%
Total data set	Any rank	81.79%	13.02%	2.57%	14.40%	4.55%	5.13%	1.55%
(n = 49,244)	Rank 1	79.38%	7.66%	1.24%	9.91%	2.01%	2.59%	1.25%

Firms ranking the constraint as a limit on output, as a percentage of all firms, including those who did not answer the question at all. Respondents were allowed to give one or more responses, hence shares do not sum to 100%.

Table 4: Small and large firms' investment constraints

		Inadequate net return	Shortage of internal finance	Inability to raise external finance	Cost of finance	Uncertainty about demand	Shortage of labour	Other	N/A
Large Firms	Any rank	47.59%	20.23%	2.99%	9.44%	49.11%	4.92%	2.07%	7.38%
(empl ≥ 200)	Rank 1	37.01%	14.94%	1.37%	4.59%	36.81%	2.54%	1.81%	8.03%
Small Firms	Any rank	33.52%	18.12%	5.07%	11.34%	58.25%	6.20%	1.58%	9.77%
(empl < 200)	Rank 1	22.95%	12.78%	2.30%	5.63%	49.01%	2.89%	1.44%	10.34%
Total data set	Any rank	38.71%	18.89%	4.30%	10.64%	54.88%	5.73%	1.76%	8.89%
(n = 49,244)	Rank 1	28.14%	13.58%	1.96%	5.25%	44.51%	2.76%	1.58%	9.49%

Firms ranking the constraint as a limit on the capital expenditure authorisations, as a percentage of all firms, including those who did not answer the question at all. Respondents were allowed to give one or more responses, hence shares do not sum to 100%.

Table 5: Variability and persistence of financial constraints

	Unconstrained in t		Constrained in t		Total	
Unconstrained in t-1	22,785	90.45%	2,407	9.55%	25,192	100%
Constrained in t-1	2,377	36.68%	4,103	63.32%	6,480	100%
Total	25,162	79.45%	6,510	20.55%	31,672	100%

Number and share of responding firms reporting either shortage of internal finance or inability to raise external finance as a factor likely to limit capital expenditure over the next twelve months.

Table 6: Association of capacity restrictions and financial constraints

		Capacity restrictions					
		Not restricted		Restricted		Total	
Financial constraints	Not constrained	33,835	87.26%	4,941	12.74%	38,776	100%
	Internal finance	6,384	79.26%	1,670	20.74%	8,054	100%
	External finance	1,694	79.94%	425	20.06%	2,119	100%
	Total	41,913	85.63%	7,036	14.37%	48,949	100%
		Association Tests					
		Pearson's test:		Chi2(2) = 404.24, P < 0.0005			
		Likelihood ratio test:		Chi2(2) = 375.38, P < 0.0005			
		Fisher's exact test:		P < 0.0005			

Rows: Number of responding firms reporting (1) neither shortage of internal finance, nor inability of external finance ("not constrained"), (2) shortage of internal finance, but no inability to obtain external finance ("internal finance") and (3) inability to obtain external finance ("external finance") as a factor likely to limit capital expenditure over the next twelve months. Columns: number of firms reporting plant capacity as likely to limit output over the next 4 months. Percentages relate to row sums.

Table 7: All firms - association of capacity restrictions and financial constraints, conditional on state of capacity restrictions in the previous period

Case 1: No capacity restrictions in previous period		**Capacity restrictions**					
		Not restricted		Restricted		Total	
Financial constraints	Not constrained	20,656	93.69%	1,392	6.31%	22,048	100%
	Internal finance	3,718	89.20%	450	10.80%	4,168	100%
	External finance	1,005	88.55%	130	11.45%	1,135	100%
	Total	25,379	92.79%	1,972	7.21%	27,351	100%
		Association Tests					
		Pearson's test:		Chi2(2) = 137.18, P < 0.0005			
		Likelihood ratio test:		Chi2(2) = 124.07, P < 0.0005			
		Fisher's exact test:		P < 0.0005			
Case 2: Capacity restrictions in previous period		**Capacity restrictions**					
		Not restricted		Restricted		Total	
Financial constraints	Not constrained	1,616	49.60%	1,642	50.40%	3,258	100%
	Internal finance	385	39.29%	595	60.71%	980	100%
	External finance	97	38.49%	155	61.51%	252	100%
	Total	2,098	46.73%	2,392	53.27%	4,490	100%
		Association Tests					
		Pearson's test:		Chi2(2) = 39.47, P < 0.0005			
		Likelihood ratio test:		Chi2(2) = 39.76, P < 0.0005			
		Fisher's exact test:		P < 0.0005			

See notes to Table 6. Tabulations and association tests are done separately for firms that did not report capacity constraints in the previous period and those that did.

Table 8: Small firms - association of capacity restrictions and financial constraints, conditional on state of capacity restrictions in the previous period

Case 1: No capacity restrictions in previous period		**Capacity restrictions**					
		Not restricted		Restricted		Total	
Financial constraints	Not constrained	13,346	94.04%	846	5.96%	14,192	100%
	Internal finance	2,171	89.45%	256	10.55%	2,427	100%
	External finance	772	89.15%	94	10.85%	866	100%
	Total	16,289	93.16%	1,196	6.84%	17,485	100%
		Association Tests					
		Pearson's test:		Chi2(2) = 91.47, P < 0.0005			
		Likelihood ratio test:		Chi2(2) = 82.16, P < 0.0005			
		Fisher's exact test:		P < 0.0005			
Case 2: Capacity restrictions in previous period		**Capacity restrictions**					
		Not restricted		Restricted		Total	
Financial constraints	Not constrained	1,002	53.84%	859	46.16%	1,861	100%
	Internal finance	212	40.38%	313	59.62%	525	100%
	External finance	65	39.39%	100	60.61%	165	100%
	Total	1,279	50.14%	1,272	49.86%	2,551	100%
		Association Tests					
		Pearson's test:		Chi2(2) = 37.82, P < 0.0005			
		Likelihood ratio test:		Chi2(2) = 38.01, P < 0.0005			
		Fisher's exact test:		P < 0.0005			

See notes to Table 6. Tabulations and association tests are done separately for firms that did not report capacity constraints in the previous period and those that did. A firm is considered as "small" if the number of employees is less than 200.

Table 9: Large firms - association of capacity restrictions and financial constraints, conditional on state of capacity restrictions in the previous period

Case 1: No capacity restrictions in previous period		**Capacity restrictions**					
		Not restricted		Restricted		Total	
Financial constraints	Not constrained	7,310	93.05%	546	6.95%	7,856	100%
	Internal finance	1,547	88.86%	194	11.14%	1,741	100%
	External finance	233	86.62%	36	13.38%	269	100%
	Total	9,090	92.13%	776	7.87%	9,866	100%
		Association Tests					
		Pearson's test:		Chi2(2) = 137.18, P < 0.0005			
		Likelihood ratio test:				Chi2(2) = 124.07, P < 0.0005	
		Fisher's exact test:		P < 0.0005			
Case 2: Capacity restrictions in previous period		**Capacity restrictions**					
		Not restricted		Restricted		Total	
Financial constraints	Not constrained	614	43.95%	783	56.05%	1,397	100%
	Internal finance	173	38.02%	282	61.98%	455	100%
	External finance	32	36.78%	55	63.22%	87	100%
	Total	819	42.24%	1,120	57.76%	1,939	100%
		Association Tests					
		Pearson's test:		Chi2(2) = 6.06, P = 0.048			
		Likelihood ratio test:				Chi2(2) = 6.10, P = 0.047	
		Fisher's exact test:		P = 0.049			

See notes to Table 6. Tabulations and association tests are done separately for firms that did not report capacity constraints in the previous period and those that did. A firm is considered as "large" if the number of employees is 200 or more.

Table 10: Survivor function and completion probabilities for the entire sample

Time	**Beg. total**	**Completed**	**Net lost**	**Completion rates**	**Survivor function**	**Std. dev.**
1	1431	856	133	0.5982	0.4018	0.0138
2	442	216	43	0.4887	0.2055	0.0122
3	183	63	16	0.3443	0.1347	0.0106
4	104	40	11	0.3846	0.0829	0.0090
5	53	12	7	0.2264	0.0641	0.0083
6	34	13	4	0.3824	0.0396	0.0074
7	17	3	2	0.1765	0.0326	0.0072
8	12	3	3	0.2500	0.0245	0.0061
9	6	3	0	0.5000	0.0122	.

Table 11: Composition of sub-samples

Sub-Sample	No. of experiences	Times at risk	Incidence rates
All Firms	1,431	2,291	0.528
Small Firms	887	1,365	0.559
Large Firms	544	926	0.482
Shortage of internal finance	363	625	0.467
No shortage of internal finance	1,068	1,666	0.551
Shortage of internal or external finance	407	703	0.472
No shortage of internal or external finance	1,024	1,588	0.553

Table 12: Proportional hazard model

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)
large (empl. ≥ 200)	-0.183*** {0.833} (0.063)		-0.187*** {0.829} (0.063)	-0.229*** {0.796} (0.074)		-0.185*** {0.831} (0.063)	-0.209*** {0.811} (0.075)
fin(1) (Shortage of internal finance)		-0.192*** {0.826} (0.072)	-0.196*** {0.822} (0.072)	-0.260*** {0.771} (0.090)			
*large*fin(1)* (Interaction term)				0.171 {1.186} (0.147)			
fin(2) (Shortage of internal or external finance)					-0.181*** {0.834} (0.068)	-0.184*** {0.832} (0.068)	-0.216** {0.806} (0.087)
*large*fin(2)* (Interaction term)							0.086 {1.090} (0.138)
Duration time dummies	9	9	9	9	9	9	9
Sector dummies	no	no	no	no	no	no	no
Dummies for time origin of spells	no	no	no	no	no	no	no
No. of spells	1,431	1,431	1,431	1,431	1,431	1,431	1,431
No. of firms	862	862	862	862	862	862	862
No. firm quarters	2,290	2,290	2,290	2,290	2,290	2,290	2,290

Cox duration model with grouped data for spells of capacity restrictions, estimated as a binary regression model using the complementary log-log function as link function; see Sect. III for further explanations. A spell is classified as pertaining to a financially constrained firm if, at the time when the spell starts, the firm reports financial constraints. The dummy variable *fin(1)* takes a value of 1 if a firm reports shortage of internal finance in the answer to question 16c and zero otherwise. The dummy variable *fin(2)* takes a value of 1 if the firm reports either shortage of internal finance or inability to raise external finance and zero otherwise. Likewise, a spell is classified as belonging to a large firm if the firm has 200 employees or more at the beginning of the spell. The first entry gives the estimated coefficients. The term in curly brackets translates this coefficient into a hazard ratio. The third figure, in round brackets, indicates the robust standard deviations, taking into account stochastic dependence between spells generated by the same firm. The coefficient estimate, divided by the standard deviation, is asymptotically standard normal, with *** indicating significance at the 1% level, and ** significance at the 5% level. One observation had to be dropped because the longest duration interval (13 quarters) predicts the event perfectly.

Table 13: Proportional hazard model controlling for sector heterogeneity

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Large (empl. ≥ 200)	-0.156** {0.855} (0.067)		-0.162** {0.851} (0.066)	-0.209*** {0.811} (0.077)		-0.160** {0.852} (0.066)	-0.197** {0.821} (0.078)
fin(1) (Shortage of internal finance)		-0.206*** {0.814} (0.071)	-0.210*** {0.810} (0.071)	-0.287*** {0.751} (0.089)			
*large*fin(1)* (Interaction term)				0.203 {1.225} (0.145)			
fin(2) (Shortage of internal or external finance)					-0.187*** {0.830} (0.068)	-0.189*** {0.827} (0.068)	-0.242*** {0.785} (0.087)
*large*fin(2)* (Interaction term)							0.139 {1.149} (0.139)
Duration time dummies	9	9	9	9	9	9	9
Sector dummies	20	20	20	20	20	20	20
Dummies for time origin of spells	no	no	no	no	no	no	no
No. of spells	1,429	1,429	1,429	1,429	1,429	1,429	1,429
No. of firms	861	861	861	861	861	861	861
No. firm quarters	2,288	2,288	2,288	2,288	2,288	2,288	2,288

See notes to Table 12. Additionally, the regressions summarised in this table use 20 dummies representing SIC (1980) 2-digit sectors. One observation had to be dropped because the longest duration interval (13 quarters) predicts the event perfectly. Two more observations and one sector (manufacturing of office machinery and data processing) were dropped because the sector dummy predicts the event perfectly.

Table 14: Proportional hazard model controlling for sector heterogeneity and business cycle effects

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Large (empl. ≥ 200)	-0.216** {0.806} (0.068)		-0.215*** {0.806} (0.068)	-0.245*** {0.782} (0.080)		0.213*** {0.807} (0.068)	-0.229*** {0.795} (0.081)
fin(1) (Shortage of internal finance)		-0.199*** {0.820} (0.073)	-0.197*** {0.821} (0.073)	-0.245*** {0.783} (0.090)			
*large*fin(1)* (Interaction term)				0.126 {1.135} (0.152)			
fin(2) (Shortage of internal or external finance)					-0.172** {0.841} (0.068)	-0.169** {0.844} (0.068)	-0.193** {0.825} (0.086)
*large*fin(2)* (Interaction term)							-0.061 {1.063} (0.143)
Duration time dummies	9	9	9	9	9	9	9
Sector dummies	20	20	20	20	20	20	20
Dummies for time origin of spells	41	41	41	41	41	41	41
No. of spells	1,429	1,429	1,429	1,429	1,429	1,429	1,429
No. of firms	861	861	861	861	861	861	861
No. firm quarters	2,288	2,288	2,288	2,288	2,288	2,288	2,288

See notes to Table 12. Additionally, the regressions summarised in this table use 20 dummies representing SIC (1980) 2-digit sectors, as well as 41 dummies indicating the time origin of the spell. One observation had to be dropped because the longest duration interval (13 quarters) predicts the event perfectly. Two more observations and one sector (manufacturing of office machinery and data processing) were dropped because the sector dummy predicts the event perfectly.

Table 15: Proportional hazard model – separate estimates for large and for small firms

Coefficient	(1) all firms	(2) small firms only	(3) large firms only	(4) all firms	(5) small firms only	(6) large firms only
fin(1)	-0.192*** {0.826} (0.072)	-0.257*** {0.774} (0.089)	-0.096 {0.909} (0.118)			
fin(2)				-0.181*** {0.834} (0.068)	-0.212** {0.809} (0.086)	-0.136 {0.873} (0.107)
Duration time dummies	9	9	9	9	9	9
No. of spells	1,431	887	544	1,431	887	544
No. of firms	862	527	349	862	527	349
No. firm quarters	2,290	1,364	926	2,290	1,364	926

See notes to Table 12. Different from the estimations shown in Table 12, 13 and 14, baseline hazards for large and small firms are estimated separately. One observation had to be dropped because the longest duration interval (13 quarters) predicts the event perfectly.