// NO.22-033 | 08/2022

# DISCUSSION PAPER

// FELIX BRACHT AND DIRK CZARNITZKI

# Patent Collateral and Access to Debt

Leibniz Association

ZEW

# Patent Collateral and Access to Debt*

Felix Bracht[a,†] and Dirk Czarnitzki[a, b, c ‡]

[a] *KU Leuven, Dept. of Management, Strategy and Innovation, Leuven, Belgium*

[b] *Center for R&D Monitoring (ECOOM) at KU Leuven, Belgium*

[c] *Centre for European Economic Research (ZEW), Mannheim, Germany*

This version: August 3, 2022

**Abstract**

We investigate how intangible capital in form of intellectual property, such as patents, might mitigate financing constraints. While scholars have already argued that patents might have a signalling value reducing information asymmetries between borrowers and lenders, we quantify the value of using patents as collateral with regard to capital access. Although this mechanism of patents in financing further R&D is not new, we are the first to provide a treatment effects study of patent collateral and access to capital. We make use of mandatory collateral registry data in Sweden and the Netherlands to construct panels combining firm-level financial data and patent measures. Estimating conditional difference-in-difference regressions on firms' debt allows deducting treatment effects of using patents as collateral. We find that patent pledging enables Swedish (Dutch) firms to borrow about 21% (26%) more than in the counterfactual situation in which no patents would have been used as collateral. We also find that the collateral value of patents is higher than their signalling value, and a back-of-the-envelope scenario calculation shows that Dutch (Swedish) firms could raise more than € 7 (€ 10) billion additional debt capital if the complete patent portfolios would be pledged, all else constant.

**Keywords:** Financing Constraints, Collateral, Intangible Assets, Patents, Treatment Effects Estimation
**JEL Codes:** O30, O34, G31

*We gratefully acknowledge financial support from the European Patent Office (Academic Research Programme). Czarnitzki also acknowledges financial support from the Research Foundation Flanders (FWO, grant G0C5921N). We thank Georg von Grävenitz, Andrew A. Toole, Hans Degryse and Steven Vanhaverbeke and conference participants at the EPIP 2021 and EPO workshop participants for valuable comments.

†KU Leuven, Naamsestraat 69, BE–3000 Leuven; E-mail: felix.bracht@kuleuven.be.

‡KU Leuven, Naamsestraat 69, BE–3000 Leuven; E-Mail: dirk.czarnitzki@kuleuven.be.

# 1 Introduction

Innovation is an important source of economic growth, especially for developed countries (Romer 1990, Aghion & Howitt 1990). However, investments in research and development (R&D) are hampered by capital restrictions (Nelson 1959, Arrow 1972). Given the inherent uncertainty of R&D projects, R&D performers are better informed about the expected outcome of their R&D projects than potential lenders. This information asymmetry can raise transaction costs to an extent that socially desirable innovation projects are not implemented as the cost of external capital rendered them privately unprofitable (Hall & Lerner 2010). Therefore, many innovative companies are financially constrained (Czarnitzki & Hottenrott 2011).

The current literature on financing constraints is mainly focused on establishing empirically the existence of financing constraints, and to lesser extent on how to mitigate them. Examples of the latter are analyses of the institutional framework, e.g. banking practice, and the relationships between firms and investors (Beck et al. 2007). Czarnitzki & Hottenrott (2017) have suggested that management practices in form of R&D collaboration may help to attenuade financing constraints. Moreover, Hottenrott et al. (2016) show that patents reduce financing constraints by disclosing information to investors, described as the signaling value of patents. In addition to the signalling value of patents, however, firms can also pledge patents for loan collateral to ease access to finance. This channel has attracted surprisingly little attention in the empirical literature.[1] The theoretical literature points out that investors can use collateral as a screening device that mitigates adverse selection (Bester 1985). Hence, patents pledged as collateral, provide incentives for lenders to commit funding and, at the same time, leave the ownership of patents to borrowers (Steijvers & Voordeckers 2009). Moreover, the loss of importance of tangible assets in modern knowledge economies (Goldfinger 1997) forces firms to resort to intangibles for collateral.

[1] One might also think of selling or licensing patents. However, in both cases firms will lose their patent or reduce its competitiveness. Moreover, small firms which are mostly affected by financing constraints are less diversified, and could thus lose significant parts of their business model by selling / licensing patents.

In this paper, we estimate treatment effects of patent pledging on the pledgor's access to external capital as measured by debt at the firm level. We obtained information on all pledged patents in Sweden and the Netherlands and constructed two panel databases including financial data. Conditional Difference-in-difference (CDiD) analyses for the matched samples of similar non-pledging Swedish and Dutch firms reveal significant increase in the levels of debt following the pledging event. Estimated results show that the patent pledging event causes an increase in debt by about 34% for Dutch pawners and about 20% for Swedish pawners, respectively. These relative changes correspond to higher debt of about 1.4 million euro in the Netherlands and 1.2 million euro in Sweden. However, descriptive statistics show that only a few patenting firms in both countries pledge patents. A back-to-envelope calculation shows that patent owners could raise more than 5 billion euro in the Netherlands and more than 13 billion euro in Sweden if all firms pledge their complete patent portfolios, all else constant. Thus, patents pledged as loan collateral may provide a fruitful source of external financing.

Our regressions also allow comparing the signaling value and the collateral value of patents with regard to debt. We find that the patents' collateral value exceeds their signaling value for firms in the Netherlands but not for firms in Sweden.

Our findings contribute to the vast literature on financing constraints. Among others, Harhoff (2000) and Brown et al. (2009) provide evidence that innovative firms are financially constrained. Our results show that firms can access external finance by offering patents as loan collateral, hence mitigate financing constraints. Moreover, we contribute to the scarce literature on patent pledging. Mann (2018) provides descriptive evidence that mature US firms pledging patents as collateral have significantly higher total debt. Our results reinforce these findings in the framework of a treatment effects study with both public and private firms in Europe and suggest that collateralized patents causally help firms to access more debt. In addition, our findings can also be interpreted as a contribution to the large literature on patent valuation (Bloom & Van Reenen 2002, ?, Czarnitzki et al. 2006, Gambardella et al. 2008). The estimated treatment effects reflect a minimum value of the pledged patent as lenders are willing to supply additional capital for these collateralized patents in loan contracts.

The rest of the paper is organized as follows: In Section 2 we explain our conceptual framework including the empirical identification strategy. In Section ?? we present a description of the data including data sources, descriptive statistics and the construction of a control group. Section 4 presents and discusses our findings. Finally, Section 5 concludes on implications of our results.

# 2 Conceptual framework and empirical identification strategy

We estimate the impact of patent pledging on firms' access to debt. Specifically, we apply a conditional difference-in-difference (CDiD) framework to estimate the treatment effect of patent collateralization in a loan negotiation. Thus, we compare the debt level of a firm after the event of a patent pledge with the debt level before this event. As the debt level might be affected by other exogenous macroeconomic characteristics relevant to the firm, we use non-patent-pledging firms as control group in the regression analysis.

To address the selection into the group of pawners, we perform matching to find similar non-pledging firms that are comparable in the pre-treatment period. Specifically, we apply a Mahalanobis distance match in the pre–treatment period on debt, equity, the patent stock and the number of forward citations the firms' patent portfolio receives in the future as well as firms' age and sector. By conducting such a matching in the pre-treatment period, we establish a quasi–experimental setting in which the treatment group and the control group had, on average, in the past similar demands for debt and currently possess similar equity. Furthermore, the patent stock and the forward citations to this patent stock control for the potential collateral that the firms could offer to lenders in terms of quantity and quality of their intellectual assets. Thus, we interpret positive coefficients for the patent pledging event as estimates of the additional capital that firms could raise because of pleding patents.

We implement the Mahalanobis distance matching as nearest neighbor matching in which we draw up to two nearest neighbors per treated firm. We use a caliper restriction to prevent bad matches, i.e. large Mahalanobis distances, which might introduce bias and draw the neighbors without replacement (Abadie & Spiess 2021).

In the following, we regress debt on a set of indicators for the periods pre- and post-pledging event for the matched sample. The change of patents collateral status allows controlling for firm-fixed effects. Therefore, any time-invariant firm characteristics, such as management quality or ownership structure, that may be related to firms' access to debt will be differenced out. The specification for the difference-in-difference regression is:

$$y_{it} = \sum_{k} \beta_1 PP_{it} + \beta_2 X_{it-1} + \beta_3 d_t + \alpha_i + \varepsilon_{it} \tag{1}$$

Specifying that $t = 0$ is the last pre-treatment period and thus also the period used for matching, the following timeline applies $t = (-2, -1, 0, 1, 2, 3, +4)$. $y_{it}$ is the natural logarithm of firm $i$'s debt in year $t$. $PP_{it} = 1$ if a patent has been pledged for all $k \geq t$ periods. $X_{it-1}$ is a vector of time-varying firm-level characteristics that might influence access to debt. We use the one-year lag of firms equity controlling for differences in capital between pledging and non-pledging firms. Furthermore, we control for differences in firm size, measured by the natural log of employees, because it is an important determinant for financing constraints (Hadlock & Pierce 2010). We include the natural logarithm of firms' patent stock to capture patents' signaling value to investors (Hottenrott et al. 2016). Last, we include the natural logarithm of the average number of forward citations of firms' annual patent portfolios. This measure serves as a proxy for the quality of firms intangible assets. $d_t$ are a set of time dummies capturing macro-economic changes, and $\alpha_i$ are firm-fixed effects capturing time-invariant differences across firms.

It is possible that the impact of patent pledging varies over time. Therefore, in a second step, we estimate a variation of Equation (1) with multiple pre-pledge and post-pledge indicators for patent pledging firms. This is useful for gauging the overall pattern of the impact of patent collateral. In addition, the coefficients for the pre-pledge periods serve as direct test of the common trend assumption. We thus regress debt on a set of indicators for the years since any patents have been pledged, ranging from $t = -2$ to $t = +4$. The estimation equation is:

$$y_{it} = \sum_{\tau=-2,\tau\neq 0}^{+4} \gamma_\tau PP_{i\tau} + \beta_2 X_{it-1} + d_t + \alpha_i + \varepsilon_{it} \tag{2}$$

$PP_{i\tau}$ is an indicator equal one if a firm pledged patents $\tau$ years after or $-\tau$ later if $\tau$ is negative, and zero otherwise. We include indicators for $\tau = -2$ before the pledging event up to 4+ years after the pledging patents. We omit the indicator the year before the pledging event ($\tau = 0$), so the estimated coefficients should be interpreted as the change relative to the year before the pledging event. Other specifications are identical to Equation 1 as described above.

The set-up of our matching routine and the fixed-effects within regression conforms to the recent suggestions of Abadie & Spiess (2021) who argue that standard errors in CDiD applications are biased if the matching is not done without replacement and the subsequent regression does not include all covariates used for the matching. We therefore believe that we establish state-of-the-art inference.

# 3 Data Sources and Descriptive Statistics

## 3.1 Data sources

The empirical analysis is based on detailed firm–level information covering balance sheet and income statement data combined with information on patents owned by the respective firms. Moreover, the analysis utilizes information on pledged patents. The registration of pledged patents is determined by the national patent law and is not mandatory in most countries. However, the Swedish and Dutch patent offices are one of the few national patent offices where the registration of collateralized patents is mandatory (Ministry of Justice Stockholm 1967, The Minister of Justice Den Haag 1995). Thus, we restrict our sample to Swedish and Dutch firms.

To construct our data, we make use of the Orbis Global and Orbis IP databases combining rich firm-level and patent-level information. Importantly, Orbis does not only cover listed companies but also private firms. We obtained historical financial data together with filed patents for all Dutch and Swedish companies. Second, we gained access to detailed information about all pledged national patents and valid EP-patents from the Dutch and Swedish Patent Offices. The database contains information about the date the patent was pledged and the patent owner at the pledging date. Information on pledgors covers firm names and addresses, allowing us to match patent pledgors with historical financial data and information on non-pledged patents from Orbis IP. Third, we gather data on the number of forward citations for all patents from PATSTAT.[2] The total number of forward citations that patents receive is a common proxy for the quality or technological importance of patents (Trajtenberg 1990, Hall et al. 2001). We average the number of forward citations over firms' annual patent stocks to proxy the quality of the entire patent portfolio.

Finally, we construct two separate panels for Swedish and Dutch firms, containing detailed financial data together with their stock of patents, the average number forward citations of the patent portfolio and the number of pledged patents on a yearly base. The patent stock is constructed according to the pertpetual inventory method. This means it measures the accumulated yearly number of patent applications of the focal firm depreciated at a rate of 15 percent as common in the literature (Cuneo & Mairesse 1983).

[2]We normalize the total number of forward citations by the average number of citations patents receive with the same filing year and technical field.

## 3.2 Descriptive Statistics

We restrict our data to patenting firms, as non-patenting firms are considered irrelevant for the treatment effects analysis. Furthermore, we have dropped all sectors in which no firm pledged a patent in our period under review. Finally, all financial variables have been trimmed at the 1% level on each side of the distribution to eliminate influential observations.[3]

The final Dutch sample includes 8650 non-pledging firms and 186 patent-pledging firms observed between 1994 and 2018. Firms in the sample pledged patents between 1995 and 2017. In total, the Dutch panel contains about 100,000 firm-year observations. The Swedish sample includes 7226 non-pledging firms and 130 patent pledging firms observed between 1997 and 2018. Firms in the sample pledged patents between 1998 and 2016. For Sweden, our final data contains almost 90,000 firm–year observations.

Tables 1 and 2 show the summary statistics for the sample of Dutch and Swedish patent-pledging firms and patentees that do not pledge any patent, respectively. Patent-pledging firms in Sweden and the Netherlands show a similar age structure with an average of around 20 years. However, Swedish pledgors are larger then their Dutch counterparts, showing on average more employees and total assets. Non-pledging firms differ in all dimensions from firms offering patents for loan collateral, which suggest a selection of firms into the group of pawners. To address potential selection effects, we conduct a matching analysis to balance the covariates among the treatment and selected control group in the pre-treatment period.

## 3.3 Matching

Tables 3 and 4 show the descriptive statistics for non-pledging firms and pledging firms in the year before patents have been pledged, i.e. the pre-treatment period. Both samples include only the first pledging event per firm since subsequent patent pledging of firms might be endogenous. The mean values of the debt variable and all covariates are statistically different between the groups in the unmatched samples (Tables 4 and 3). To balance

[3]The debt variable has been trimmed at 2% level due to high number of outliers.

the covariates between patent-pleding and non-pledging firms, we apply a Mahalanobis distance match on pre-treatment debt, equity, firm age, patent stock (and its square to assign more weight to this variable in the matching procedure), and the number of forward citations of firms' patent portfolios. We require an exact match on the economic sector and year. The matching is implemented as nearest neighbor matching in which we draw up to two neighbors per treated firm. We include a caliper to avoid distant matches which might induce bias otherwise. Tables 3 and 4 show the same descriptive statistics after the matching process. The matched sample of Dutch firms includes 141 pledgors matched to 275 similar non-pledging firms. The matched sample of Swedish firms include 126 patent pledgors matched to 248 non-pledging firms. There are no significant differences between the groups for the matched variables. Consequently, patent pledging and non-pledging firms are observably similar with respect to firm characteristics determining their access to debt.

Tables 5 and 6 show the summary statistics for the matched sample of patent pledging firms, separated for the pre- and post-treatment period. The average debt levels increases signficiantly in the period following the colleratization of patents. However, other observable firm characteristics including equity, the number of employees, and the number of patents are higher in post-treatment periods as well. Therefore, the increase in debt levels could be partially explained by an increase in the size of firms. The following difference-in-difference analysis will include controls for firm's equity, employment, patent stock, and the number of forward citations of firms patent portfolio thus, account for potential size effects and effects driven by differences in patents value.

# 4 Estimation Results

## 4.1 Main Results

Table 7 presents the empirical results for the CDiD regressions on the impact of a patent pledging on the debt level for the matched sample of Dutch firms. The first two columns show the results with and without controls for the CDiD estimation. Columns 3 and 4 show the results with and without controls for the dynamic CDiD estimation taking pre-treatment dummies into account. The variable of interest "*post_pledge*" shows a positive sign with highly significant coefficients at the 5% level. Thus, firms significantly increase debt finance after pledging patents. In terms of magnitude, patent pledging firms increase debt by about 34%[4] relative to the counterfactual situation in which no patent would have been used as collateral.

Figure 1 graphically visualizes the estimated coefficients of the "dynamic" difference-in-difference analysis. Both coefficients of pre-treatment indicators are insignificant. Thus, we find no evidence for diverging trends between pledging firms and control groups of non-pledging firms in years prior the pledging event. Consequently, the estimated treatment effects are unlikely to be driven by firm specific trends in debt finance for pre-treatment periods. Most importantly, the graph shows a significant jump for firms' debt levels in post-treatment periods starting in the year of the pledging event. This shows that Dutch firms increase debt immediately after the patent collaterlization.

Table 8 presents the empirical results for the difference-in-difference regression concerning the impact of a patent pledging event on debt level for the matched sample of Swedish firms. The first two columns show the results with and without controls for the simple difference-in-difference estimation. Column 3 and 4 show the results with and without controls for the dynamic difference-in-difference estimation, respectively. The average treatment effects for the Swedish sample are smaller than for the Dutch sample. Patent pledging firms in Sweden increase debt by about 20%. Interestingly, post-treatment effects are only significant starting the second and third year following the pledging event.

[4] $100 \times \left(e^{0.29} - 1\right)$

Thus, the increase in debt occurs mainly in the third year after patents have been pledged. A possible explanation for the delay might be that collateralized loans are only taken up sequentially and not in full amount immediately. This is common in, for example, loan contracts for buildings that are under construction.

Control variables for employment and firms patent stock show a positive coefficient in both samples. This is in line with the financial literature that defines firm size as the main determinant of firms' access to debt (Hadlock & Pierce 2010). Furthermore, the positive coefficient for the patent stock confirms (Hottenrott et al. 2016) findings on the signaling value of patents to external investors. Our results show that a one percent increase in firms' patent stock is associated with a 17% increase in the debt levels of Dutch firms and 37% increase in the debt levels of Swedish firms. Thus, Dutch firms can increase their debt by pledging patents more than their Swedish counterparts. However, the signaling value of patents seems to be more pronounced in Sweden. Last, the coefficients for the number of forward citations on the portfolio level show different signs for the Dutch and Swedish samples. This is likely due to the strong correlation with the patent stock variable.[5]

[5]Unreported results where we include controls individually show a postive sign for the number of forward citations on the portfolio level in both samples. This is in line with the expectation that patents with higher underlying technological quality (value) are more likely to be pledged.

## 4.2 Placebo Test

A key assumption for the difference-in-difference analysis is the common trend assumption. In our setting, this means that in the absence of a patent pledging event, the debt levels of treatment and controls groups should have followed the same trend. To further prove the validity of our empirical design, we performe a placebo test for randomly assigned "fake" pledging events in the pre-treatment period of patent pledging Dutch and Swedish firms.[6] Afterwards the assignment of fake pledging events, we estimate the identical difference-in-difference analysis applied in our main analysis. The idea of this placebo test is that the fake pledging event should not alter firms' debt level if the firms follow the same trend in debt finance.

Tables 10 and 12 show the results of the difference-in-difference analysis using "fake" patent pledging events in pre-treatment periods for Sweden and the Netherlands receptively. In both samples the treatment indicator "*post_pledge*" show a small and insignificant coefficient. Hence, fake pledging events in pre-treatment periods do not alter firms' debt level. This further supports the assumption that firms in our main analysis follow the same trend in debt finance in years prior the patent pledging event, and that our actual treatment effects estimations are indeed causal.

[6] "Fake" pledge events have been assigned for each patent pledging firm at a random year prior the actual pledging event.

# 5 Conclusion

It is well known that many innovative companies are financially constrained. The literature shows that patents can mitigate such financial frictions through their signaling value by reducing information asymmetries between borrowers and lenders. However, patents can also serve as loan collateral and thereby improve firms' access to debt. This collateral channel has attracted surprisingly little attention in the existing literature.

In this paper, we estimate the impact of patent-pledging on firms' debt level using a quasi-experimental set-up by implemting conditional difference-in-difference regressions. Thus, we provide causal evidence for the increase in firms' debt capacity through the pledging of patents. We show for a sample of Dutch and Swedish patent filing firms that the patent pledging event causes an increase in the level of debt by about 34% for Dutch pawners and about 20% for Swedish pawners.

It is possible to translate our marginal effects into monetary values by multiplying the effect size with the firms' debt level prior to the pledging event. This implies that Dutch (Swedish) firms were able ro raise, on average, 1.38 (1.24) million additional euros debt by offering patents as loan collateral. However, our descriptive statistics show that only a few patent-filing firms pledged their patents compared to the number of patent-owning firms. This implies that innovators in Sweden and the Netherlands currently do not exhaust all financing opportunities. Specifically, non-pledging Dutch (Swedish) firms could raise addtional 5.1 billion euro (13.4 billion euro) external funding in total by offering their patents as loan collateral, all else constant.

We can also revisit prior findings on the positive signaling value of patents. Our results show that firms patent stock is associated with a 17% increase in the debt levels of Dutch firms and 37% increase in the debt levels of Swedish firms. In monetary terms, this means that the signaling value of pledged patents can explain an average increase in debt of 594 thousand euro for Dutch firms and an average increase in debt of 1.8 million euro for Swedish firms.[7] This suggests that the collateral value of patents exceeds their signaling value for firms in the Netherlands but not for firms in Sweden.

Finally, our results can also seen as contribution to the literature on patent valuation that, for example, assesses marginal effects of (quality–weighted) patent stocks on firms' market value. We offer a new method to assess minimum values of patent portfolios as our estimated treatment effects may reflect the value of patents to the extent that a lender commits additional financial resources for patents being used as collateral.

There are some important limitations to our results. First, companies do not pledge patents at random. Since we were unable to find a suitable instrument for the pledging event[8], we applied a CDiD regression for a matched sample to mitigate selection effects. However, the matching of a similar control group of non-pleding firms is based on observable firm characteristics. Thus, we cannot exclude the possibility that unobserved firm characteristics drive both firms' access to debt and the decision to pledge patents. Second, our empirical analysis is based on Dutch and Swedish firms which limits the generalizability of our results to countries with a similar economy and legal framework.

[7]The calculation of the signaling value is based on the average patent stock prior to the pledging event which is equal to 1.69 (2.91) in the Netherlands (Sweden). Adding the average number of pledged patents (2.26 in the Netherlands and 3.53 in Sweden) leads to an increase in the patent stock by 84.9% (79.44%) in the Netherlands (Sweden). Consequently, the increase in the patent stock by the number of pledged patents corresponds to an increase in debt by about 14% (29%) for Dutch (Swedish) firms.

[8]We have tried to use variation in real estate prices at the location of the companies, the distance between firms and their national patent office, regional variation in the share of relationship banks to total banks and weather shocks at the firm's location. However, neither of the purposed instruments significantly explained patent pledging.

# References


Abadie, A. & Spiess, J. (2021), 'Robust post-matching inference', *Journal of the American Statistical Association* pp. 1–13.

Aghion, P. & Howitt, P. (1990), A model of growth through creative destruction, Technical report, National Bureau of Economic Research.

Arrow, K. J. (1972), 'Economic Welfare and the Allocation of Resources for Invention', *Readings in Industrial Economics* pp. 219–236.

Beck, T. et al. (2007), Financing constraints of smes in developing countries: Evidence, determinants and solutions, *in* 'KDI 36th Anniversary International Conference', pp. 26–27.

Bester, H. (1985), 'Screening vs. rationing in credit markets with imperfect information', *The American economic review* **75**(4), 850–855.

Bloom, N. & Van Reenen, J. (2002), 'Patents, real options and firm performance', *The Economic Journal* **112**(478), C97–C116.

Brown, J. R., Fazzari, S. M. & Petersen, B. C. (2009), 'Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom', *The Journal of Finance* **64**(1), 151–185.

Cuneo, P. & Mairesse, J. (1983), 'Productivity and r&d at the firm level in french manufacturing'.

Czarnitzki, D., Hall, B. H. & Oriani, R. (2006), 'The market valuation of knowledge assets in us and european firms'.

Czarnitzki, D. & Hottenrott, H. (2011), 'R&d investment and financing constraints of small and medium-sized firms', *Small Business Economics* **36**(1), 65–83.

Czarnitzki, D. & Hottenrott, H. (2017), 'Inter-organizational collaboration and financing constraints for r&d', *Economics Letters* **161**, 15–18.

Gambardella, A., Harhoff, D. & Verspagen, B. (2008), 'The value of European patents', *European Management Review* **5**(2), 69–84.

Goldfinger, C. (1997), 'Intangible economy and its implications for statistics and statisticians', *International Statistical Review* **65**(2), 191–220.

Hadlock, C. J. & Pierce, J. R. (2010), 'New evidence on measuring financial constraints: Moving beyond the kz index', *The Review of Financial Studies* **23**(5), 1909–1940.

Hall, B. H., Jaffe, A. B. & Trajtenberg, M. (2001), The nber patent citation data file: Lessons, insights and methodological tools, Technical report, National Bureau of Economic Research.

Hall, B. H. & Lerner, J. (2010), The financing of r&d and innovation, *in* 'Handbook of the Economics of Innovation', Vol. 1, Elsevier, pp. 609–639.

Harhoff, D. (2000), Are there financing constraints for r&d and investment in german manufacturing firms?, *in* 'The economics and econometrics of innovation', Springer, pp. 399–434.

Hottenrott, H., Hall, B. H. & Czarnitzki, D. (2016), 'Patents as quality signals? the implications for financing constraints on r&d', *Economics of innovation and new technology* **25**(3), 197–217.

Mann, W. (2018), 'Creditor rights and innovation: Evidence from patent collateral', *Journal of Financial Economics* **130**(1), 25–47.

Ministry of Justice Stockholm (1967), 'Patents act (1967:837)'. Art. 95., [Last Accessed: June 15th 2018].
**URL:** *https://www.prv.se/globalassets/dokument/patent/informationsmaterial/the-patents-act---unofficial-translation.pdf*

Nelson, R. R. (1959), 'The simple economics of basic scientific research', *Journal of political economy* **67**(3), 297–306.

Romer, P. M. (1990), 'Endogenous technological change', *Journal of political Economy* **98**(5, Part 2), S71–S102.

Steijvers, T. & Voordeckers, W. (2009), 'Collateral and credit rationing: a review of recent empirical studies as a guide for future research', *Journal of Economic Surveys* **23**(5), 924–946.

The Minister of Justice Den Haag (1995), 'the dutch patents act'. Art. 67., [Last Accessed: March 25th 2022].
**URL:** *https://english.rvo.nl/sites/default/files/2013/12/ROW95_ENG_niet_officiele_vertaling_0.pdf*

Trajtenberg, M. (1990), 'A penny for your quotes: patent citations and the value of innovations', *The Rand journal of economics* pp. 172–187.

# Appendices

Table 1: Summary statistics for the Dutch sample

| | Patent pledging firms | | | | | Non-pledging firms | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max |
| Debt | 1731 | 7940.23 | 14764.48 | 0.16 | 116128.38 | 99287 | 4498.24 | 13510.72 | 0.10 | 160524.00 |
| Equity | 1731 | 4329.86 | 8416.49 | 0.00 | 68734.73 | 99287 | 4259.89 | 19074.73 | 0.00 | 405889.00 |
| Employees | 1155 | 92.74 | 169.85 | 1.00 | 1393.00 | 61087 | 62.25 | 255.55 | 1.00 | 40045.00 |
| Age | 1731 | 22.84 | 23.28 | 0.00 | 116.00 | 99287 | 22.16 | 22.90 | 0.00 | 314.00 |
| Patentstock | 1731 | 2.19 | 2.98 | 0.00 | 24.78 | 99287 | 1.13 | 12.13 | 0.00 | 1035.30 |
| Forward Cites | 1731 | 0.24 | 0.31 | 0.00 | 2.15 | 99287 | 0.17 | 0.40 | 0.00 | 13.37 |
| *N* | 1731 | | | | | 99287 | | | | |

8650 non-pledging firms and 186 patent pledging firms observed between 1994 and 2018. Firms pledge patents between 1995 and 2017. All monetary values are in Thd. Euros.

Table 2: Summary statistics for the Swedish sample

| | Patent pledging firms | | | | | Non-pledging firms | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max |
| Debt | 1439 | 10484.09 | 27095.14 | 1.02 | 196236.00 | 86890 | 4922.64 | 17076.80 | 0.87 | 204978.81 |
| Equity | 1439 | 7304.02 | 18187.47 | 0.00 | 189014.34 | 86890 | 4424.33 | 17932.23 | 0.00 | 372612.00 |
| Employees | 1365 | 89.24 | 233.53 | 0.00 | 2196.00 | 80990 | 50.77 | 192.70 | 0.00 | 9387.00 |
| Age | 1439 | 20.09 | 18.40 | 0.00 | 119.00 | 86890 | 21.77 | 19.29 | 0.00 | 119.00 |
| Patentstock | 1439 | 2.97 | 5.80 | 0.00 | 48.62 | 86890 | 1.20 | 5.58 | 0.00 | 344.16 |
| Forward Cites | 1439 | 0.36 | 0.39 | 0.00 | 2.76 | 86890 | 0.18 | 0.38 | 0.00 | 14.31 |
| *N* | 1439 | | | | | 86890 | | | | |

7226 non-pledging firms and 130 patent pledging firms observed between 1997 and 2018. Firms pledge patents between 1998 and 2016. All monetary values are in Thd. Euros.

Table 3: Summary statistics for the matched sample of Dutch firms

| | Unmatched | | | Matched | | |
|---|---|---|---|---|---|---|
| | Pledgor | Control | p>\|t\| | Pledgor | Control | p>\|t\| |
| Equity | 3948.49 | 2219.45 | 0.003 | 1514.86 | 1463.69 | 0.891 |
| Debt | 8096.03 | 3561.73 | 0.000 | 3090.16 | 2660.70 | 0.365 |
| Age | 18.77 | 21.73 | 0.074 | 14.97 | 14.44 | 0.760 |
| Patentstock | 2.43 | 1.00 | 0.000 | 1.79 | 1.47 | 0.129 |
| Patentstock$^2$ | 15.75 | 94.45 | 0.007 | 7.27 | 5.83 | 0.624 |
| Forward Cites | 0.20 | 0.13 | 0.000 | 0.17 | 0.16 | 0.690 |
| N | 186 | 89452 | | 141 | 275 | |

All monetary values are in Thd. Euros.

Table 4: Summary statistics for the matched sample of Swedish firms

| | Unmatched | | | Matched | | |
|---|---|---|---|---|---|---|
| | Pledgor | Control | p>\|t\| | Pledgor | Control | p>\|t\| |
| Equity | 5742.14 | 3632.01 | 0.173 | 3537.67 | 2463.21 | 0.332 |
| Debt | 8966.81 | 4649.05 | 0.075 | 4586.21 | 2604.76 | 0.105 |
| Age | 14.45 | 21.52 | 0.000 | 13.83 | 13.52 | 0.852 |
| Patentstock | 2.71 | 1.16 | 0.000 | 2.57 | 1.88 | 0.121 |
| Patentstock$^2$ | 26.00 | 27.80 | 0.838 | 23.93 | 15.89 | 0.406 |
| Forward Cites | 0.30 | 0.14 | 0.000 | 0.29 | 0.26 | 0.258 |
| N | 130 | 80560 | | 126 | 248 | |

All monetary values are in Thd. Euros.

Table 5: Summary statistics for patent-pledging Dutch firms

| | Pre-pledge | | | | | Post-pledge till t=4 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max |
| Debt | 199 | 4116.55 | 4579.17 | 0.18 | 20247.23 | 276 | 4864.92 | 8534.10 | 8.24 | 79489.00 |
| Equity | 199 | 2031.51 | 3190.27 | 0.00 | 16733.63 | 276 | 1979.23 | 3625.46 | 0.00 | 22379.90 |
| Employees | 199 | 35.77 | 48.72 | 1.00 | 239.00 | 276 | 30.87 | 47.43 | 1.00 | 300.00 |
| Age | 199 | 17.69 | 18.25 | 1.00 | 99.00 | 276 | 20.09 | 19.75 | 1.00 | 103.00 |
| Patentstock | 199 | 1.69 | 2.01 | 0.00 | 18.21 | 276 | 1.57 | 1.83 | 0.04 | 15.48 |
| Forward Cites | 199 | 0.22 | 0.30 | 0.00 | 2.15 | 276 | 0.22 | 0.31 | 0.00 | 2.15 |
| # Patents | 199 | 3.78 | 4.98 | 0.00 | 46.00 | 276 | 4.53 | 6.11 | 1.00 | 46.00 |
| # Pledged patents | 199 | 0.00 | 0.00 | 0.00 | 0.00 | 89 | 2.26 | 2.34 | 1.00 | 17.00 |
| *N* | 199 | | | | | 276 | | | | |

All monetary values are in Thd. Euros.

Table 6: Summary statistics for patent-pledging Swedish firms

| | Pre-pledge | | | | | Post-pledge till t=4 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max |
| Debt | 241 | 6303.78 | 13409.71 | 2.93 | 94418.00 | 401 | 6973.39 | 18888.17 | 3.03 | 133773.00 |
| Equity | 241 | 5659.17 | 15345.72 | 0.00 | 121260.00 | 401 | 4361.43 | 11113.04 | 0.00 | 80792.09 |
| Employees | 241 | 74.53 | 186.29 | 0.00 | 1114.00 | 401 | 60.65 | 167.02 | 0.00 | 1342.00 |
| Age | 241 | 16.16 | 16.59 | 1.00 | 78.00 | 401 | 16.91 | 15.92 | 1.00 | 81.00 |
| Patentstock | 241 | 2.91 | 4.38 | 0.00 | 27.60 | 401 | 2.68 | 4.79 | 0.05 | 33.46 |
| Forward Cites | 241 | 0.39 | 0.40 | 0.00 | 2.19 | 401 | 0.37 | 0.38 | 0.00 | 2.23 |
| # Patents | 241 | 6.47 | 10.43 | 0.00 | 47.00 | 401 | 6.67 | 11.29 | 1.00 | 67.00 |
| # Pledged patents | 241 | 0.00 | 0.00 | 0.00 | 0.00 | 126 | 3.53 | 6.21 | 1.00 | 43.00 |
| *N* | 241 | | | | | 401 | | | | |

All monetary values are in Thd. Euros.

Table 7: Difference-in-difference regression estimating the impact of patent pledging on debt level in the Netherlands

| | Diff-in-Diff | | Dynamic Diff-in-Diff | |
|---|---|---|---|---|
| Dep. Variable: | Log(Debt) | Log(Debt) | Log(Debt) | Log(Debt) |
| *post_pledge* | 0.28*** | 0.29*** | | |
| | (0.11) | (0.099) | | |
| *pre(t2)_pledge* | | | -0.064 | -0.059 |
| | | | (0.18) | (0.16) |
| *pre(t1)_pledge* | | | 0.016 | 0.0047 |
| | | | (0.17) | (0.16) |
| *post(t1)_pledge* | | | 0.32** | 0.32** |
| | | | (0.15) | (0.14) |
| *post(t2)_pledge* | | | 0.39** | 0.39** |
| | | | (0.16) | (0.16) |
| *post(t3)_pledge* | | | 0.28 | 0.30* |
| | | | (0.17) | (0.17) |
| *post(t4f)_pledge* | | | 0.11 | 0.11 |
| | | | (0.19) | (0.18) |
| *Log(Equity)* | | -0.021*** | | -0.019*** |
| | | (0.0041) | | (0.0041) |
| *Log(Employees)* | | 0.24*** | | 0.25*** |
| | | (0.035) | | (0.035) |
| *Log(Patent_Stock)* | | 0.17*** | | 0.15*** |
| | | (0.056) | | (0.056) |
| *Log(Forward_Cites)* | | 0.76** | | 0.76** |
| | | (0.31) | | (0.31) |
| Year FE | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES |
| F | 7.09 | 25.8 | 3.32 | 14.5 |
| R-squared | 0.82 | 0.83 | 0.82 | 0.83 |
| N | 2669 | 2669 | 2669 | 2669 |

This table presents the results for the difference-in-difference regression estimating the impact of patent pleding on firms' debt level. Regression accounts for sampling weights. Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Difference-in-difference regression estimating the impact of patent pledging on debt level in Sweden

| | Diff-in-Diff | | Dynamic Diff-in-Diff | |
|---|---|---|---|---|
| Dep. Variable: | Log(Debt) | Log(Debt) | Log(Debt) | Log(Debt) |
| *post_pledge* | 0.30*** | 0.18** | | |
| | (0.080) | (0.071) | | |
| *pre(t2)_pledge* | | | -0.15 | 0.035 |
| | | | (0.16) | (0.13) |
| *pre(t1)_pledge* | | | -0.072 | -0.011 |
| | | | (0.14) | (0.13) |
| *post(t1)_pledge* | | | 0.17 | 0.14 |
| | | | (0.11) | (0.10) |
| *post(t2)_pledge* | | | 0.11 | 0.12 |
| | | | (0.14) | (0.12) |
| *post(t3)_pledge* | | | 0.31*** | 0.28*** |
| | | | (0.12) | (0.10) |
| *post(t4f)_pledge* | | | 0.31*** | 0.21** |
| | | | (0.10) | (0.088) |
| *Log(Equity)* | | 0.013 | | 0.014 |
| | | (0.0091) | | (0.0093) |
| *Log(Employees)* | | 0.61*** | | 0.58*** |
| | | (0.033) | | (0.034) |
| *Log(Patent_Stock)* | | 0.37*** | | 0.41*** |
| | | (0.044) | | (0.051) |
| *Log(Forward_Cites)* | | -0.53*** | | -0.57*** |
| | | (0.16) | | (0.17) |
| Year FE | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES |
| F | 14.3 | 111.4 | 4.12 | 49.4 |
| R-squared | 0.88 | 0.91 | 0.88 | 0.91 |
| N | 4119 | 4119 | 4119 | 4119 |

This table presents the results for the difference-in-difference regression estimating the impact of patent pleding on firms' debt level. Regression accounts for sampling weights. Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

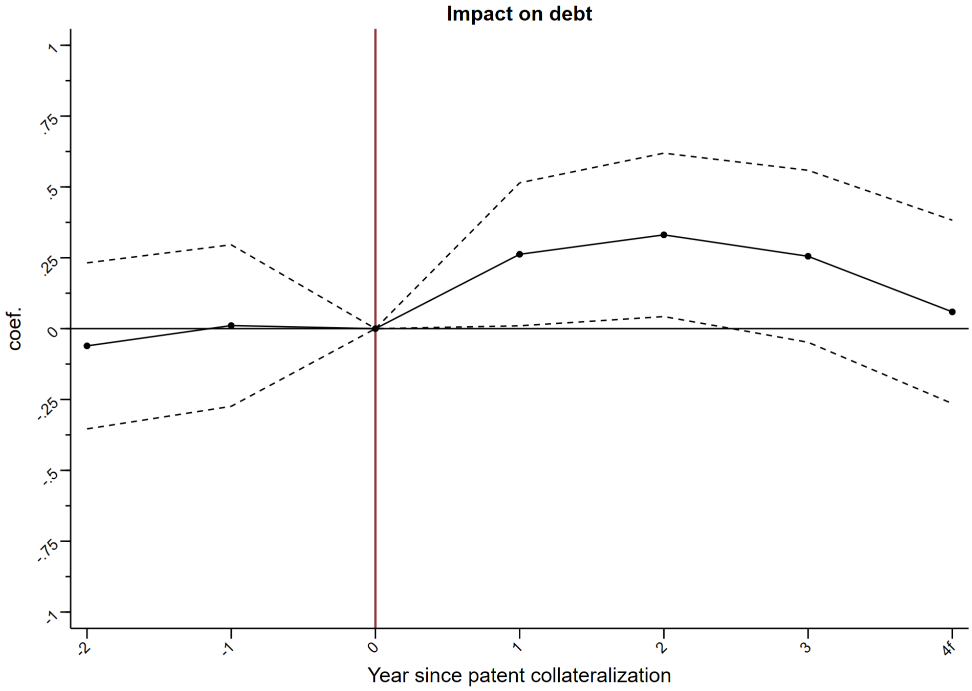


Figure 1: Coefficient plots for the dynamic difference-in-difference estimation using the Dutch sample

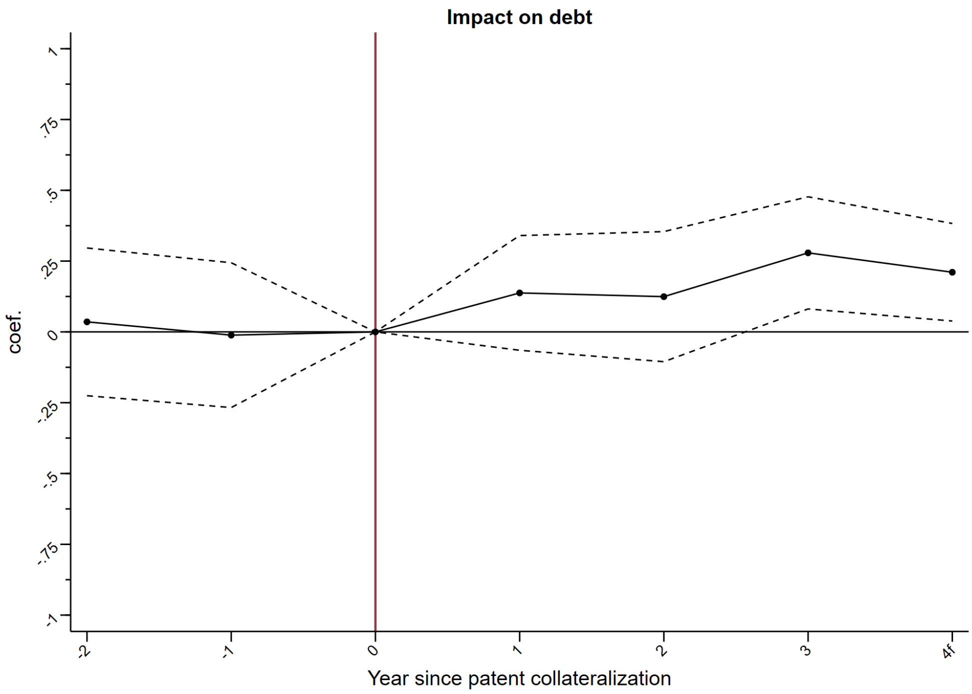


Figure 2: Coefficient plots for the dynamic difference-in-difference estimation using the Swedish sample

Table 9: Summary statistics for the Dutch placebo sample

| | Patent pledging firms | | | | | Non-pledging firms | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max |
| Debt | 1731 | 7940.23 | 14764.48 | 0.16 | 116128.38 | 99287 | 4498.24 | 13510.72 | 0.10 | 160524.00 |
| Equity | 1731 | 4329.86 | 8416.49 | 0.00 | 68734.73 | 99287 | 4259.89 | 19074.73 | 0.00 | 405889.00 |
| Employees | 1155 | 92.74 | 169.85 | 1.00 | 1393.00 | 61087 | 62.25 | 255.55 | 1.00 | 40045.00 |
| Age | 1731 | 22.84 | 23.28 | 0.00 | 116.00 | 99287 | 22.16 | 22.90 | 0.00 | 314.00 |
| Patentstock | 1731 | 2.19 | 2.98 | 0.00 | 24.78 | 99287 | 1.13 | 12.13 | 0.00 | 1035.30 |
| Forward Cites | 1731 | 0.24 | 0.31 | 0.00 | 2.15 | 99287 | 0.17 | 0.40 | 0.00 | 13.37 |
| *N* | 1731 | | | | | 99287 | | | | |

The sample includes 9064 non-pledging firms and 191 patent pledging firms with randomly assigned pledging events observed between 1994 and 2018. True pledging events have been replace by fake pledging events in periods prior the actual patent pledging event. Periods after the patent pledging events of patent pledging firms have been dropped. All monetary values are in Thd. Euros.

Table 10: Difference-in-difference regression estimating the impact of a fake pledging events in pre-treatment periods on debt level in the Netherlands

| | Diff-in-Diff | |
|---|---|---|
| Dep. Variable: | Log(Debt) | Log(Debt) |
| $post\_pledge$ | -0.072 | -0.10 |
| | (0.087) | (0.085) |
| $Log(Equity)$ | | -0.015*** |
| | | (0.0013) |
| $Log(Employees)$ | | 0.25*** |
| | | (0.0081) |
| $Log(Patent\_Stock)$ | | 0.26*** |
| | | (0.015) |
| $Log(Forward\_Cites)$ | | 0.29*** |
| | | (0.064) |
| Year FE | YES | YES |
| Firm FE | YES | YES |
| F | 0.69 | 313.9 |
| R-squared | 0.86 | 0.87 |
| N | 56148 | 56148 |

This table presents the results for the difference-in-difference regression estimating the impact of fake patent pledging events on firms' debt level. egression accounts for sampling weights. Robust standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Summary statistics for the Swedish placebo sample

| | Patent pledging firms | | | | | Non-pledging firms | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max |
| Debt | 410 | 10432.37 | 30002.43 | 1.60 | 203694.00 | 88952 | 5071.65 | 17566.38 | 0.87 | 204978.81 |
| Equity | 425 | 12868.55 | 36311.79 | -120.00 | 364397.19 | 97825 | 5220.08 | 22824.25 | -129.52 | 372612.00 |
| Employees | 413 | 179.35 | 589.17 | 0.00 | 4929.00 | 91193 | 63.60 | 330.17 | 0.00 | 40567.00 |
| Age | 441 | 15.44 | 18.23 | 0.00 | 100.00 | 98866 | 21.58 | 19.36 | 0.00 | 120.00 |
| Patentstock | 441 | 4.02 | 11.31 | 0.00 | 125.27 | 98866 | 1.31 | 6.83 | 0.00 | 410.56 |
| Forward Cites | 441 | 0.36 | 0.37 | 0.00 | 2.19 | 98866 | 0.19 | 0.38 | 0.00 | 14.31 |
| $N$ | 441 | | | | | 98866 | | | | |

The sample 7500 non-pledging firms and 123 patent pledging firms with randomly assigned pledging events observed between 1997 and 2018. True pledging events have been replace by fake pledging events in periods prior the actual patent pledging event. Periods after the patent pledging events of patent pledging firms have been dropped. All monetary values are in Thd. Euros.

Table 12: Difference-in-difference regression estimating the impact of a fake pledging events in pre-treatment periods on debt level in Sweden

| | Diff-in-Diff | |
|---|---|---|
| Dep. Variable: | Log(Debt) | Log(Debt) |
| *post_pledge* | -0.15* | -0.11 |
| | (0.087) | (0.076) |
| $Log(Equity)$ | | 0.011*** |
| | | (0.0023) |
| $Log(Employees)$ | | 0.65*** |
| | | (0.011) |
| $Log(Patent\_Stock)$ | | 0.22*** |
| | | (0.012) |
| $Log(Forward\_Cites)$ | | 0.16*** |
| | | (0.047) |
| Year FE | YES | YES |
| Firm FE | YES | YES |
| F | 2.84 | 1031.9 |
| R-squared | 0.88 | 0.91 |
| N | 75492 | 75492 |

This table presents the results for the difference-in-difference regression estimating the impact of fake patent pledging events on firms' debt level. egression accounts for sampling weights. Robust standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Download ZEW Discussion Papers:

https://www.zew.de/en/publications/zew-discussion-papers

or see:

https://www.ssrn.com/link/ZEW-Ctr-Euro-Econ-Research.html
https://ideas.repec.org/s/zbw/zewdip.html

//
IMPRINT

**ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim**

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de