Online appendix
Criminals, bankruptcy, and cost of debt

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We present the tables at the end of each online appendix.

Content

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1 Online Appendix A: The types of employees

1.1 Individuals

We aim to identify individuals who associate with the bankruptcy likelihood. In Table OA1, we add the criminal records of the highest salary-ranked non-CEO employees, one at a time. The results depict the uniqueness of the CEO (Bennedsen et al. 2020). Only the criminal record of *one person*, the CEO, is associated with the bankruptcy likelihood. The result speaks to our setup in the main analysis separating the criminal record of the CEO from the rest of the workforce in each firm.

1.2 Non-CEO executives

In section 4.3 of the manuscript, we identify groups of employees with decision-making authorities based on their salary received from the firm. In the following, we change our strategy for the identification of these employees and use job positions when available. When our data do not record job positions, we use the salary. We identify non-CEO executives as follows.

1. We identify a person as a non-CEO executive if the person is filed as an executive with the Danish Business Authority, but is not the CEO.[1] If a firm has none identified non-CEO executive(s), then
2. We obtain data on working positions, through the Integrated Database for Labor Market Research (IDAN database), i.e. the administrative dataset we use to link employees to employers. The classifications in the IDAN database are based on the International Labour Organization's (ILO's) recommendations. Specifically, we classify a person as a non-CEO

[1] Information on firm executives is publicly available at https://datacvr.virk.dk/data/

executive if she is a non-CEO "top manager" or a non-CEO "employee with a managerial role."[2] If a firm has zero identified non-CEO executive(s), then

3. We use a person's taxable income received from the firm to identify non-CEO executives. Specifically, we classify a person as a non-CEO executive if she is among the top-10% paid non-CEOs. Consequently, for firms with 12–19 employees, we identify one non-CEO executive. For firms with 20–29 employees, we identify two non-CEO executives, and so forth. From this step, we cap the maximum number of non-CEO executives at five.

From the procedure we identify on average (a median of) 3.5 (2.0) non-CEO executives per firm. The variable *%EXEC_record* denotes the percentage of non-CEO executives with criminal records and has a mean of 14.3%. The variable $\%EMPL\_record_{other\_employees}$ measures the percentage of non-CEO and non-executive employees with criminal records. The mean of $\%EMPL\_record_{other\_employees}$ is 17.2%, slightly higher than the mean of *%EMPL_record* (17.1%) used in the main analysis.

Panel A of Table OA2 presents the regression tables. We add one layer at a time to unravel the information conveyed by each layer. We do not find that criminal records of non-CEO executives are associated with the bankruptcy likelihood. $\%EMPL\_record_{other\_employees}$ is significantly associated with bankruptcy, consistent with our main analysis reported in Table 5 of the manuscript. This supports our main analysis setup, in which we group information on all non-CEO employees in one variable, *%EMPL_record*.

[2] From the IDAN database, we use the variables "STILL" code 31, and "SOC_STATUS_KODE" code 131. A description of the STILL variable is available at https://www.dst.dk/da/Statistik/dokumentation/Times/ida-databasen/ida-ansaettelser/still. A description of the SOC_STATUS_KODE variable is available at https://www.dst.dk/da/TilSalg/Forskningsservice/Dokumentation/hoejkvalitetsvariable/befolkningens-tilknytning-til-arbejdsmarkedet--ras-/soc-status-kode. Both are in Danish.

As we add the layers in the firm, criminal records of non-CEO executives and employees, the coefficient on *CEO_record* decreases. We make several inferences of this. First, one channel through which record holder CEOs influence a firm's risk is to employ managers and employees who share their beliefs.[3] Second, CEOs influence firm risk through more channels than simply employing certain employees. This is emphasized through the observation that the coefficient on *CEO_record* remains relatively large as we add additional layers to the estimations. Third, the positive coefficient on $\%EMPL\_record_{other\_employees}$ suggests that criminal records of employees relate to firm risk, beyond the criminal record of the CEO.

Panel B of Table OA2 shows the out-of-sample prediction accuracies of (1) using the criminal records of the CEO only (Specification A), (2) using the criminal records of the CEO and the non-CEO executives (Specification B), and (3) using the criminal records of the CEO and the employees (Specification C). We find that the prediction accuracy of the specification including the CEO and the employees (Specification C) outperforms the specification based on the CEO only (Model A) (p-value = 0.08). The specifications A and C are not significantly different from Specification B.

[3] This inference is comparable to Bender et al. (2018), who in a similar vein show that a large portion of the effect of management scores on productivity is accounted for by the hiring of better-quality workers.

Table OA1. Uniqueness of the CEO

	Dependent variable: *Bankrupt*$_t$ N=103,410, π*Bankrupt*=0.0127						
	Reported coefficients: Marginal effects at mean					H0: *CEO=EXEC*	
						χ^2	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CEO_record$_t$	0.0045**				0.0045**		
	(2.21)				(2.17)		
#1 EXEC_record$_t$		0.0010			0.0005	1.57	0.21
		(0.44)			(0.24)		
#2 EXEC_record$_t$			-0.0006		-0.0008	2.86	0.09*
			(-0.28)		(-0.37)		
#3 EXEC_record$_t$				0.0004	0.0003	1.76	0.18
				(0.19)	(0.14)		
%EMPL_record$_{other\ employees,\ t}$	0.0216***	0.0235***	0.0246***	0.0235***	0.0222***		
	(2.68)	(2.92)	(3.05)	(2.90)	(2.71)		
Firm and Year FE	Yes	Yes	Yes	Yes	Yes		
ACC controls	Ohlson	Ohlson	Ohlson	Ohlson	Ohlson		
Firm variables	Yes	Yes	Yes	Yes	Yes		
Person variables	Yes	Yes	Yes	Yes	Yes		
Pseudo R sq.	0.2457	0.2436	0.2437	0.2435	0.2460		
In-sample AUC	0.8958	0.8947	0.8946	0.8948	0.8961		

This table examines whether criminal records of CEOs, non-CEO executives, and employees predict firm bankruptcy. *CEO_record* indicates that the CEO has a criminal record. *#1, #2, and #3 EXEC_record* indicates that the highest, second highest, and third highest ranked non-CEO has a criminal record, respectively. The ranks are based on the salary received from the firm over year *t*. *%EMPL_record*$_{other\ employees}$ is the proportion of employees with criminal records, excluding CEO and the top-three ranked non-CEO executives. The statistics presented in columns 6 and 7 test for coefficient equality between *CEO_record* and the *EXEC_record* variable in question (*#1*, *#2*, and *#3*, respectively). The tests are based on the estimation in column 5. We estimate the regressions applying the Ohlson model with a hazard estimation (Shumway 2001). The Ohlson model controls, *firm variables*, and *person variables*, as well as industry and year fixed effects, are estimated but for brevity not reported. Accounting ratios are winsorized at the lower and upper 1% level. The *z*-statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

Table OA2. Non-CEO executives and bankruptcy likelihood

Panel A: Regression tables

	Dependent variable: $Bankrupt_t$ Reported coefficients: Marginal effects at mean		
	(1)	(2)	(3)
CEO_record_t	0.0052^{**}	0.0051^{**}	0.0044^{**}
	(2.57)	(2.47)	(2.16)
$\%EXEC\_record_t$		0.0037	0.0026
		(1.27)	(0.86)
$\%EMPL\_record_{other\_employees,\ t}$			0.0202^{**}
			(2.45)
Industry and year FE	Yes	Yes	Yes
ACC	Ohlson	Ohlson	Ohlson
Firm and *person variables*	Yes	Yes	Yes
N	103,774	103,774	103,774
Pseudo R sq.	0.2424	0.2431	0.2459
In-sample AUC	0.8944	0.8949	0.8961

Panel B: Out-of-sample fit

Specification	**A**	**B**	**C**
CEO_record	Yes	Yes	Yes
%EXEC_record		Yes	
$\%EMPL\_record_{other\ employees}$			Yes
Out-of-sample AUC	0.8683	0.8683	0.8691
		(2)-(1)	(3)-(1)
AUC difference (basis points)		0	8
χ^2		0.00	3.10^{*}
			(3)-(2)
AUC difference (basis points)			8
χ^2			2.50

This table examines whether criminal records of CEOs, non-CEO executives, and other employees predict bankruptcies. We estimate the regressions applying the Ohlson model with a hazard estimation (Shumway 2001). Panel A presents the regression results. Panel B presents the out-of-sample AUC using three different specifications. We present AUC differences in basis points for ease of interpretation. *CEO_record* indicates that the CEO has a criminal record. *%EXEC_record* is the percentage of non-CEO executives with criminal records. $\%\ EMPL\_record_{other\_employees}$ is the percentage of employees (other than CEOs and executives) with criminal records. The Ohlson model controls, *Firm variables*, and *Person variables*, as well as industry and year fixed effects, are estimated but for brevity not reported. Accounting ratios are winsorized at the lower and upper 1% level. The *z*-statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

2 Online Appendix B: Additional tests

2.1 Subsample analyses

We conduct several subsample analyses for further insights and report them in Table OA3. Panel A presents the results including the person-specific control variables and Panel B without. Specifically, we split our sample based on firm size as measured by total assets, firm size as measured by the number of full-time equivalent employees, governance structure as measured by whether the CEO serves on the board, and whether the CEO has a criminal record. We describe each of these subsample tests below.

Firm size: In columns 1 and 2, we split the sample conditioned by the size of total assets. We adjust total assets for inflation,[4] calculate each firm's average inflation adjusted assets over all its annual observations in the dataset, and split our sample by firms above and below the median in the sample. In columns 3 and 4, we split the sample conditioned by the number of full-time equivalent employees. Specifically, we calculate each firm's average number of employees over all its annual observations in the dataset, and split our sample by firms above and below the median in the sample.

In Panel A, we generally find that the criminal records of employees significantly predict bankruptcies for small firms. In Panel B, where we do exclude other person-specific control variables, the criminal records of employees predict bankruptcies both for large and small firms (the coefficient estimates are significantly positive) and significantly increase the prediction accuracy (the out-of-sample AUC) in both subsamples. We note that the coefficient estimates are not significantly different across these subsamples.

[4] We divide total assets by the price index for the year to make the size measure comparable over time We use the net consumer price index available at https://www.dst.dk/da/Statistik/emner/priser-og-forbrug/forbrugerpriser/nettoprisindeks.

Governance: In columns 5 and 6, we split the sample conditioned by firm' governance structure. Specifically, we split the sample by firms for which the CEO serves, or not, on the board. In Denmark, our setting, CEO duality is not allowed. However, CEOs often serve on the board, which we use as an indicator for poor governance structures. Both in Panels A and B, the criminal records of both CEOs and employees predict bankruptcies only for firms with poor governance structures (for firms in which the CEO serves on the board). The out-of-sample prediction accuracy increases significantly only for the sample with weak governance structures, and only when we exclude the personal controls from the specifications.

CEO record: In columns 7 and 8, we split the sample conditioned by the firms in which the CEO has a criminal record. In Panel A, the criminal records of employees predict bankruptcies in firms where the CEO does not have a criminal record (significant at the 10% level). However, we note that the sample of firms with record-holder CEOs is relatively small, and the estimate of the marginal effect at the mean for these firms is larger than the comparable estimate for non-record-holder CEO firms (although the difference is not statistically significant). In Panel B, criminal records of employees predict bankruptcies in both subsamples (p-value = 0.051 for the subsample in which the CEO has a record and p-value<0.01 for the subsample without such CEOs). The criminal records of employees significantly improve the out-of-sample prediction accuracy for firms with nonrecord-holder CEOs, although this only holds for the specification without the personal controls.

In conclusion, the results provide some evidence that the effect of employees with criminal records is concentrated in small firms with poor governance structures, and in firms in which the CEO does not have a criminal record.

2.2 Financial performance

The analyses in the manuscript document that criminal records of CEOs and employees are positively associated with firm risk, as measured by the bankruptcy likelihood. Increased firm risk could be desirable, if it in turn is associated with better financial performance. We hence examine whether firms with a CEO with a criminal record, and more employees with criminal records, have better financial performance.

2.2.1 Firm efficiency using data envelopment analysis

We use data envelopment analysis (DEA) (Demerjian et al. 2012) and estimate an optimization model where output, in our model revenue,[5] is a function of inputs, in our model tangible fixed assets, intangible fixed assets, number of employees (full-time equivalents), costs of goods sold, and SG&A. The three stock variables are measured at the beginning of year t (denoted $t-1$) and the two flow variables are measured over year t (denoted t). We perform the estimation per industry-year and require at least 100 observations per industry-year. From this procedure, we obtain a firm efficiency score between zero and one, for which one denotes the firm-year observations, which are on the frontier and thus have the highest firm efficiency given the inputs. The mean (median) firm efficiency score is 0.77 (0.77). About 8.0% of the observations are on the frontier.

Following Demerjian et al. (2012), we parse out total firm efficiency into firm efficiency and managerial (and employee) efficiency. Demerjian et al. (2012) uses a Tobit regression and regress the firm efficiency score on firm-specific variables, such as size and cash flow proxies, and use the

[5] As revenue is rarely published in the annual report due to exemption rules, we complement our revenue data extracted from annual reports with proprietary revenue data from tax filings through Statistics Denmark. We use revenue as published in the annual report if available. If not available, we use revenue data from tax filings.

residuals as a measure of managerial ability. However, as noted by Chen et al. (2018) two-step regressions produce biased results. We thus apply a Tobit regression and regress in a one-step procedure the firm efficiency score on the firm-specific variables and our variables that measure criminal records of CEOs and employees. The measures pertaining to the criminal records of CEOs and employees, respectively, thus capture how they relate to firm efficiency *controlling* for firm-specific variables.

The firm-specific variables are as follows. Consistent with Demerjian et al. (2012), we control for the logarithm of total assets, the logarithm of firm age, and a variable indicating positive free cash flows. Demerjian et al. (2012) use a variable that measures firm-specific market share. However, we argue that market share is an outcome of firm efficiency and instead use a measure of market concentration. Specifically, we generate the Herfindahl–Hirschman index formed by industry-year using total assets of all Danish firms (e.g., Bernard 2016). The Herfindahl–Hirschman index computationally takes a high value for industry-years with a low concentration. For the ease of interpretation, we multiply the index by -1 and call it *MarketConcentration*. Finally, Demerjian et al. (2012) control for two variables measuring firm complexity, the business segment concentration and an indicator for sales in foreign currency. Our data do not provide this information. Instead, we proxy firm complexity with the number of subsidiaries.

Table OA4 reports the results. *CEO_record* and *%EMPL_record* are not significantly associated with firm efficiency. Whereas we in the main analysis of the manuscript find that criminal records of CEOs and employees are positively associated with firm risk, we do not find that they translate to superior firm financial performance in terms of firm efficiency. These results align with the findings of Law and Mills (2019). Their study concludes that financial advisors with criminal records impose a risk to investors without conveying performance benefits. Our results suggest that these results permeate a countrywide sample of firms in many industries.

We find that the firm efficiency increases with the proportion of employees with a college degree *(%EMPL_HighEduc*) and a CEO's corruption index at the country of ancestry (*CEO_CorrupIndex*), and decreases with the age of the CEO and the employees (*CEO_log(age)* and *%EMPL_log(age)*).

2.2.2 Extraordinary firm performance using Gazelle Prices

Criminal records of CEOs and employees could be associated with a wider dispersion of financial performance, and therefore correlate with more extraordinary and right-skewed performance outcomes, although not associated with better financial efficiency on average. For example, Levine and Rubinstein (2017) document that individuals engaging in illicit behavior (among other traits) are more likely to become incorporated business owners (entrepreneurs), and that the income dispersion of entrepreneurs is wider than for salaried workers.

We use the winning of *Gazelle Prices* as an observable outcome of firms with extraordinary performance.[6] These prices are awarded annually by *Børsen*, a Danish business newspaper, and award recipients are celebrated at a large event. Firms flag Gazelle awards on their websites and on social media.[7] The prices are awarded to firms meeting the following objective criteria based on the last four annual reports.[8] (1) Revenues of at least DKK 1 million (EUR 133,333) or gross profits of at least DKK 500,000 (EUR 66,667) in the first year of measurement. (2) At least four annual reports must be published and must cover 12 months. (3) The growth in revenues, or gross profits if revenues are not disclosed, must be positive for all of the four years, and the total growth over the four-year period must be at least 100%. (4) The sum of the operating profit must be

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[6] Other countries than Denmark award similar prices for high growth companies or study the "gazelles." See for instance González-Uribe and Reyes (2021), https://growingbusinessawards.co.uk/ (UK example), and https://www.ft.com/content/8b37a92b-15e6-4b9c-8427-315a8b5f4332 (European example).

[7] Search for #BørsenGazelle on LinkedIn

[8] See the criteria at https://borsen.dk/gazelle/om-borsen-gazelle/ (in Danish)

positive. (5) Only incorporated firms can win the price. We generate the variable *Gazelle*, which takes the value one for the firm-year in which a firm fulfils all the above criteria, and zero otherwise.

In Table OA5, we regress *Gazelle* on *CEO_record*, *%EMPL_record*, and controls, using a logit estimation. We find that both *CEO_record* and *%EMPL_record* are positively associated with *Gazelle*, indicating that the propensity of winning a *Gazelle Price* increases when a firm's CEO has a criminal record, and increases with the proportion of employees with criminal records. The results thus suggest that criminal records of CEOs and employees are associated with extraordinary and right-skewed firm performance.

In addition, we find that the propensity to win the *Gazelle Price* increases with the proportion of employees with a college or university degree (*%EMPL_HighEduc*) and the CEO's corruption index at country of ancestry (*CEO_CorrupIndex*) and decreases with the proportion of female employees (*%EMPL_female*) and the age of CEOs and employees (*CEO_log(age)* and *%EMPL_log(age)*).

2.3 Changes in employees

2.3.1 Changes in accounting figures

We test whether current changes in the percentage of employees with criminal records predict future corporate decisions, in terms of changes in investments, debt, and growth-related variables. Specifically, we estimate changes in the accounting variables over three periods from one to three years (from $t - 1$ to t, $t + 1$, and $t + 2$, respectively) as a function of current changes in the proportion of employees with criminal records (Δ*%EMPL_record*) and CEO changes (Δ*CEO_record*) (from the end of year $t - 1$ to the end of year t). To isolate the effect of criminal records, we control for levels of the CEO and employee variables (*%EMPL_record* and *CEO_record*), lagged changes in the accounting variables (changes over year t – 1), and the person-specific variables (*Person variables*). We regress changes on changes, which mitigates concerns about correlated omitted variables and autocorrelation in the error term (Jiang 2008).

Table OA6 shows that increases in Δ*%EMPL_record* predict increases in all of the accounting variables, mostly for all prediction horizons. Specifically, Δ*%EMPL_record* relates positively to changes to the capital investments (Δ*CapEx*), size (Δ*TA*), liabilities (Δ*TL*), Revenues (Δ*Revenue*), and EBIT (Δ*EBIT*). The results suggest that changes in the employee composition predict corporate decisions, which manifest in the accounting figures in the future. We argue that growth in these variables captures changes to the firm risk. Δ*CEO_record* does not predict changes in the accounting figures, potentially because such changes are rare, as outlined in section 4.6 of the manuscript.

We note that Δ*%EMPL_record* positively predicts changes in EBIT, which could suggest that criminal record-holder employees associate with higher firm profitability. However, the firm's total assets grow faster than the EBIT (as measured by the coefficient on Δ*%EMPL_record* in columns 4–6 vs columns 13–15), leading to lower profitability in terms of returns on assets.

2.3.2 Bankruptcy prediction

We address a concern regarding our results being driven by a firm fixed effect. Our dependent variable, *Bankrupt*, is a dichotomous variable that for many firms does not variate over time (most firms do not go bankrupt). Therefore, we are generally limited from exploring within-firm changes (such as estimations with firm fixed effects). However, we can examine whether changes in the percentage of employees with criminal records are associated with future bankruptcy. To test this, we decompose the variable *%EMPL_record* for year t into a stock variable at the beginning of a period and a flow variable that measures the changes over a period. We examine periods ranging from one to three years. For completeness, we apply a similar decomposition of the variable *%CEO_record*.

Table OA7 presents the results. The columns 1 through 3 show the results controlling for the *person variables*. The results in column 3 provides some evidence that changes over three years in the percentage of employees with criminal records predict bankruptcies (*p*-value = 0.07). The change variables over one and two years in columns 1 and 2, respectively, are not significantly different from zero, although all the coefficient estimates are positive. In columns 4 through 6, excluding the *person variables* from the specifications, changes over three years are significantly associated with bankruptcy (p-value = 0.029), and changes over one and two years are marginally significant (p-values in the range 0.058–0.094). The effects are incremental to the effects of the stock variable (*%EMPL_record* at the beginning of the period). All the lagged *%EMPL_record* variables (lagged by one, two, and three years) are statistically significant.

We do not find that CEO turnovers (when CEOs with criminal records replace CEOs without, or vice versa) predict bankruptcies, although the point estimates are positive. We note that CEO turnovers are rare, as outlined in section 4.6 of the manuscript.

The findings provide some evidence that changes in employees with criminal records predict bankruptcies, in addition to the level of employees with criminal records, although the evidence is not statistically strong. This suggests that criminal records of employees capture more than merely a firm fixed effect.

2.4 Long-term likelihood of bankruptcy estimation

We explore the ability of criminal records to predict bankruptcies over longer horizons. Specifically, we estimate Eq. (1) with *Bankrupt* for the years $t + 1$, $t + 2$, and $t + 3$ and report the results in Table OA8. In columns 1–3, including all controls, we do not find that criminal records of employees or CEOs predict bankruptcies. In columns 4–6, excluding the person-specific variables from the specification, we find that criminal records to some extent predict bankruptcies over long horizons. The criminal records of CEOs (*CEO_record*) lose their predictive power already at short prediction horizons. *CEO_record* is only marginally significant when we extend the prediction horizon by one year (significant at the 10% level) and is insignificant for longer horizons. Criminal records of employees (*%EMPL_record*), however, have predictive power for longer horizons. *%EMPL_record* predicts bankruptcies for year $t + 1$ (significant at the 5% level) and marginally predicts bankruptcies for year $t + 2$ and year $t + 3$ (significant at the 10% level). We note that the coefficients on *CEO_record* and *%EMPL_record* are generally stable when we extend the prediction horizon.

2.5 Propensity-score matching

Bankrupt firms are significantly different from nonbankrupt firms in several aspects which could lead to functional form misspecification (Shipman et al. 2017). Therefore, we use propensity-score matching and match bankrupt firms with nonbankrupt firms that do not go bankrupt within the following three years, within the same industry-year. We match on the likelihood of bankruptcy using Eq. (1) excluding the criminal record of CEOs and employees from the specification. That is, we match on all the control variables. We use a caliper of 0.005, 1:1 matching, and match without replacement. Panel A of Table OA9 shows the descriptive statistics of the matched samples. Bankrupt firms are more likely to have a CEO with a criminal record and more employees with criminal records than matched firms.

In Panel B, we include the accounting variables in the second stage to remove any remaining differences. That is, we estimate Eq. (1) with the matched sample. We find that any prior conclusions remain unchanged. In untabulated analyses, we generate two alternative propensity-score matched samples. First, we match on the propensity of having a CEO with a criminal record, instead of matching on the bankruptcy likelihood, and find similar results. Second, we match on the probability of having a high proportion of employees with criminal records (defined as above the within year median of *%EMPL_record*), instead of matching on bankruptcy likelihood, and find similar results. In conclusion, bankrupt firms being significantly different on observables to nonbankrupt firms does not drive our main results.

Table OA3. Subsample analyses

	Size based on total assets		Size based on the number of employees		Governance: The CEO serves on the board		The CEO has a record	
	Large	Small	Large	Small	No	Yes	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: With person controls								
CEO_record$_t$	0.0043	0.0049	0.0031	0.0057**	0.0054	0.0041*	n.a.	n.a.
	(1.57)	(1.58)	(1.02)	(2.04)	(1.55)	(1.91)		
%EMPL_record$_t$	0.0163	0.0254**	0.0221	0.0222**	0.0192	0.0198**	0.0286	0.0177*
	(1.27)	(2.17)	(1.60)	(2.05)	(1.12)	(2.29)	(1.60)	(1.95)
ACC, *Firm*, and *Person* vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	51,905	51,869	51,906	51,868	19,527	83,470	19,403	84,214
Pseudo R sq.	0.2531	0.2424	0.2490	0.2493	0.2297	0.2503	0.2503	0.2431
In-sample AUC	0.9068	0.8887	0.9006	0.8938	0.8992	0.8965	0.8879	0.8973
Mean(bankr)	0.0094	0.0166	0.0112	0.0148	0.0079	0.0133	0.0186	0.0111
Out-of-sample AUC	0.8441	0.8513	0.8482	0.8469	0.7685	0.8432	0.8181	0.8635
Incremental AUC (basis points)	17	9	30	11	-8	11	-29	10
p-value	0.22	0.39	>0.01***	0.38	0.87	0.32	0.16	0.12
Panel B: Without person controls								
CEO_record$_t$	0.0045*	0.0049	0.0035	0.0057**	0.0054	0.0044**	n.a.	n.a.
	(1.69)	(1.60)	(1.14)	(2.06)	(1.56)	(2.04)		
%EMPL_record$_t$	0.0197*	0.0325***	0.0268**	0.0287***	0.0194	0.0253***	0.0300*	0.0241***
	(1.75)	(3.10)	(2.24)	(2.94)	(1.34)	(3.26)	(1.95)	(2.96)
ACC and *Firm* vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	51,905	51,869	51,906	51,868	19,527	83,470	19,403	84,214
Pseudo R sq.	0.2478	0.2404	0.2454	0.2461	0.2250	0.2468	0.2457	0.2401
In-sample AUC	0.9036	0.8880	0.8987	0.8926	0.8990	0.8950	0.8865	0.8961
Mean(bankr)	0.0094	0.0166	0.0112	0.0148	0.0079	0.0133	0.0186	0.0111
Out-of-sample AUC	0.8516	0.8568	0.8519	0.8563	0.7867	0.8482	0.8384	0.8663
Incremental AUC (basis points)	28	28	34	31	-9	25	4	25
p-value	0.06*	0.03**	0.01**	0.03**	0.76	0.04**	0.82	>0.01***

This table examines whether the criminal records of CEOs and employees predict bankruptcies in subsamples. We estimate the regressions applying the Ohlson model with a hazard estimation (Shumway 2001). We present incremental AUC in basis points for ease of interpretation. *CEO_record* indicates that the CEO has a criminal record. *%EMPL_record* is the percentage of employees with criminal records. All control variables from Eq. (1), as well as industry and year fixed effects, are estimated but for brevity not reported. Accounting ratios are winsorized at the lower and upper 1% level. The *z*-statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

Table OA4. Criminal records and firm efficiency

	Expected sign	Dependent variable: *FirmEfficiency*$_t$ (1)	(2)
CEO_record$_t$	?	-0.0005	-0.0008
		(-0.27)	(-0.42)
%EMPL_record$_t$	?	-0.0142*	-0.0103
		(-1.94)	(-1.30)
Log(TA)$_{t-1}$	+	0.0168***	0.0172***
		(15.63)	(15.76)
POS_FCFF$_t$	+	0.0325***	0.0327***
		(30.11)	(30.38)
Log(1+FirmAge)$_t$	+	-0.0085***	-0.0067***
		(-6.37)	(-4.91)
Log(1+SUBS)$_t$	-	0.0094***	0.0089***
		(4.55)	(4.32)
MarketConcentration$_t$	-	-0.0338***	-0.0326***
		(-5.49)	(-5.25)
CEO_HighEduc$_t$			-0.0019
			(-0.71)
%EMPL_HighEduc$_t$			0.0459***
			(3.81)
CEO_Female$_t$			0.0011
			(0.33)
%EMPL_Female$_t$			-0.0029
			(-0.57)
CEO_log(Age)$_t$			-0.0130***
			(-3.23)
%EMPL_log(Age)$_t$			-0.0194**
			(-2.27)
CEO_Married$_t$			-0.0000
			(-0.02)
%EMPL_Married$_t$			-0.0051
			(-0.62)
CEO_CorrupIndex$_t$			0.0004**
			(2.37)
%EMPL_CorrupIndex$_t$			0.0000
			(0.16)
Year FE		Yes	Yes
Industry FE		Yes	Yes
N		84,039	84,039

This table examines whether criminal records of CEOs and employees are associated with firm efficiency. *FirmEfficiency* is the measure derived from the data envelopment analysis described in Section 2.2.1 of the online appendix and measures the financial efficiency. *CEO_record* indicates that the CEO has a criminal record. *%EMPL_recond* is the percentage of employees with criminal records. *Log(TA)* is the logarithm of total assets. *POS_FCFF* indicates that the free cash flow to the firm is positive. *Log(1+FirmAge)* is the logarithm of 1 + firm age, measured as years since the firm was incorporated. *Log(1+SUBS)* is the logarithm of 1 + the number of subsidiaries. *MarketConcentration* is the Herfindahl-Hirschman index formed by industry-year using total assets of all incorporated Danish firms multiplied by -1. The estimation is a tobit regression with firm clustered standard errors. *t* statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

Table OA5. Propensity to win the "Gazelle Award" awarded to successful and fast-growing companies

	Dependent variable: $Gazelle_t$ Reported coefficients: Marginal effects at mean	
Control variables:	Firm efficiency	Ohlson
	(1)	(2)
CEO_record_t	0.0051**	0.0074***
	(2.29)	(3.54)
$\%EMPL\_record_t$	0.0416***	0.0487***
	(3.86)	(5.46)
$CEO\_HighEduc_t$	0.0019	0.0019
	(0.65)	(0.66)
$\%EMPL\_HighEduc_t$	0.0489***	0.0415***
	(5.69)	(5.82)
CEO_Female_t	-0.0022	0.0006
	(-0.54)	(0.18)
$\%EMPL\_Female_t$	-0.0294***	-0.0235***
	(-3.21)	(-3.02)
$CEO\_log(Age)_t$	-0.0547***	-0.0518***
	(-9.45)	(-9.36)
$\%EMPL\_log(Age)_t$	-0.0738***	-0.0684***
	(-5.42)	(-6.12)
$CEO\_Married_t$	0.0000	0.0009
	(0.00)	(0.46)
$\%EMPL\_Married_t$	0.0165	0.0042
	(1.62)	(0.49)
$CEO\_CorrupIndex_t$	0.0004***	0.0003***
	(3.03)	(3.28)
$\%EMPL\_CorrupIndex_t$	0.0002	0.0003
	(0.60)	(1.26)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Additional firm vars.	Yes	Yes
N	89,018	103,774
Pseudo R sq.	0.0730	0.1588
In-sample AUC	0.7178	0.8123
π $Gazelle_t$	0.0462	0.0499

The table examines whether CEO's and employees' criminal records are associated with a firm's propensity to win the "Gazelle Price", which is awarded to successful and fast-growing companies. *Gazelle* indicates that a firm fulfills all the requirements for winning the Gazelle Price in the year and is hence awarded the price. This indicates that the firm's performance over the past years was extraordinary. The formal definition of *Gazelle* is provided in the text (Section 2.2.2). Column 1 controls for the variables used in Table OA4. Column 2 controls for the Ohlson model variables, which are defined in Appendix A of the manuscript. We control for the additional *firm variables* (wealth of owners, number of employees, and earnings volatility) in both estimations. These estimations are logistic regressions with firm and year clustered standard errors. The *z*-statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

Table OA6. Changes in employee composition and future changes in accounting numbers

Panel A: Changes in investments and balance sheet items

Dependent variable=	Future changes in *CapEx*, scaled by TA_{t-1}			Future changes in *TA*, scaled by TA_{t-1}			Future changes in *TL*, scaled by TA_{t-1}		
Changes over the period:	1 year *t*-1 to *t*	2 years *t*-1 to *t*+1	3 years *t*-1 to *t*+2	1 year *t*-1 to *t*	2 years *t*-1 to *t*+1	3 years *t*-1 to *t*+2	1 year *t*-1 to t	2 years *t*-1 to *t*+1	3 years *t*-1 to *t*+2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEO_record_{t-1}	0.0010	0.0017	0.0011	0.0032	0.0090*	0.0108	0.0020	0.0060	0.0093
	(1.73)	(1.51)	(0.84)	(1.45)	(1.93)	(1.29)	(1.01)	(1.58)	(1.51)
$\Delta CEO\_record_{[t-1\,;\,t]}$	0.0011	0.0017	-0.0051	0.0030	-0.0007	-0.0204	0.0038	-0.0038	-0.0092
	(0.30)	(0.37)	(-1.54)	(0.33)	(-0.05)	(-1.52)	(0.51)	(-0.31)	(-0.78)
$\%EMPL\_record_{t-1}$	0.0144**	0.0063	-0.0000	0.0431***	0.0571**	0.0686*	0.0349***	0.0354*	0.0266
	(2.65)	(0.66)	(-0.00)	(4.20)	(2.55)	(1.82)	(3.93)	(2.14)	(0.97)
$\Delta\%EMPL\_record_{[t-1\,;\,t]}$	0.0322**	0.0474***	0.0130	0.1330***	0.2204***	0.1931***	0.0929***	0.1600***	0.1165***
	(2.84)	(5.14)	(0.92)	(6.63)	(7.26)	(5.68)	(6.36)	(6.38)	(4.09)
$\Delta CapEx_{[t-2\,;\,t-1]}$ / TA_{t-2}	-0.0008	-0.0009	-0.0011	-0.0001	-0.0009**	-0.0008**	0.0004	-0.0002	-0.0002
	(-0.90)	(-1.01)	(-1.49)	(-0.45)	(-2.91)	(-2.59)	(1.43)	(-0.47)	(-0.59)
$\Delta TA_{[t-2\,;\,t-1]}$ / TA_{t-2}	-0.0244***	-0.0280**	-0.0274**	0.0018	0.0126	0.0311	-0.0019	0.0179	0.0359
	(-3.07)	(-2.62)	(-2.40)	(0.28)	(0.95)	(1.40)	(-0.23)	(1.17)	(1.59)
$\Delta TL_{[t-2\,;\,t-1]}$ / TA_{t-2}	-0.0394***	-0.0514***	-0.0569***	-0.0360***	-0.0562***	-0.0925***	-0.0303**	-0.0631***	-0.0928***
	(-3.36)	(-3.70)	(-3.76)	(-4.12)	(-4.84)	(-4.36)	(-2.56)	(-3.38)	(-3.47)
$\Delta Revenue_{[t-2\,;\,t-1]}$ / TA_{t-2}	0.0020**	0.0009	0.0021***	0.0100***	0.0143***	0.0195***	0.0085***	0.0112***	0.0142***
	(2.83)	(1.35)	(3.88)	(6.57)	(6.56)	(6.67)	(6.69)	(6.57)	(5.71)
$\Delta EBIT_{[t-2\,;\,t-1]}$ / TA_{t-2}	0.0602***	0.0564***	0.0470***	0.0395***	0.0915***	0.0771**	0.0020	0.0433**	0.0231
	(8.80)	(6.27)	(5.17)	(3.40)	(4.18)	(2.83)	(0.18)	(2.51)	(1.04)
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person variables.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88,789	83,651	73,945	89,337	85,339	76,793	89,337	85,339	76,793
Adjusted R sq.	0.0399	0.0506	0.0550	0.0471	0.0668	0.0741	0.0292	0.0429	0.0496

(Table OA6 con'd)

Panel B: Changes in income statement items

Dependent variable=	Future changes in *Revenue*, scaled by TA_{t-1}			Future changes in *EBIT*, scaled by TA_{t-1}		
Changes over the period:	1 year *t*-1 to *t*	2 years *t*-1 to *t*+1	3 years *t*-1 to *t*+2	1 year *t*-1 to *t*	2 years *t*-1 to *t*+1	3 years *t*-1 to *t*+2
	(10)	(11)	(12)	(13)	(14)	(15)
CEO_record_{t-1}	-0.0091	-0.0041	-0.0120	0.0003	0.0001	-0.0017
	(-1.35)	(-0.33)	(-0.65)	(0.23)	(0.03)	(-0.87)
$\Delta CEO\_record_{[t-1\,;\,t]}$	-0.0238	-0.0194	-0.0621*	0.0017	-0.0006	-0.0060
	(-0.90)	(-0.77)	(-1.88)	(0.42)	(-0.12)	(-0.90)
$\%EMPL\_record_{t-1}$	0.1101**	0.1067**	0.1059	0.0003	-0.0060	-0.0073
	(2.55)	(2.30)	(1.05)	(0.05)	(-0.63)	(-0.47)
$\Delta\%EMPL\_record_{[t-1\,;\,t]}$	0.5136***	0.6728***	0.6162***	0.0450***	0.0453***	0.0397*
	(6.90)	(7.17)	(6.78)	(3.58)	(4.19)	(1.82)
$\Delta CapEx_{[t-2\,;\,t-1]} / TA_{t-2}$	-0.0021**	-0.0022***	-0.0037***	-0.0005***	-0.0001*	0.0001
	(-2.57)	(-3.08)	(-5.18)	(-8.18)	(-1.92)	(0.85)
$\Delta TA_{[t-2\,;\,t-1]} / TA_{t-2}$	0.0560	0.0826	0.0925	-0.0372**	-0.0512**	-0.0522**
	(1.48)	(1.56)	(1.59)	(-2.93)	(-2.80)	(-2.56)
$\Delta TL_{[t-2\,;\,t-1]} / TA_{t-2}$	0.1350***	0.1129**	0.1219**	0.0527***	0.0702***	0.0729***
	(3.50)	(2.42)	(2.39)	(3.90)	(3.79)	(3.52)
$\Delta Revenue_{[t-2\,;\,t-1]} / TA_{t-2}$	-0.0964***	-0.1093***	-0.1293***	-0.0002	-0.0014	-0.0006
	(-12.62)	(-14.80)	(-14.45)	(-0.25)	(-1.64)	(-0.56)
$\Delta EBIT_{[t-2\,;\,t-1]} / TA_{t-2}$	0.1140***	0.1579***	0.1488**	-0.1413***	-0.1813***	-0.2160***
	(4.62)	(4.40)	(2.64)	(-16.25)	(-13.16)	(-11.21)
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Person vars.	Yes	Yes	Yes	Yes	Yes	Yes
N	89,320	85,250	76,382	89,337	85,329	76,782
Adjusted R sq.	0.0701	0.0809	0.0853	0.0736	0.0945	0.1062

This table shows whether changes in the percentage of employees with criminal records predict future changes to accounting variables. *CEO_record* indicates that the CEO has a criminal record. *%EMPL_record* measures the percentage of employees with criminal records. *CapEx* is capital expenditures, calculated as changes in tangible and intangible assets plus depreciation and amortization. *TA* is total assets. *TL* is total liabilities. *Revenue* is revenues as reported in the annual report if available, and otherwise revenues as reported to the tax authorities. *EBIT* is earnings before interest and tax. The estimation is an OLS estimation with standard errors clustered by firm and year. *Person variables*, intercept, industry and year fixed effects are estimated but for brevity not reported. Accounting ratios are winsorized at the lower and upper 1% level. The *t*-statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

Table OA7. Levels and changes estimations

	Dependent variable: $Bankrupt_t$					
	Reported coefficients: Marginal effects at mean					
	With person variables			Without person variables		
Lagged variable at time	*t* - 1	*t* - 2	*t* - 3	*t* - 1	*t* - 2	*t* - 3
Changes over the period	[*t* - 1 ; *t*]	[*t* - 2 ; *t*]	[*t* - 3 ; *t*]	[*t* - 1 ; *t*]	[*t* - 2 ; *t*]	[*t* - 3 ; *t*]
j =	1	2	3	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)
CEO_record_{t-j}	0.0044**	0.0043**	0.0042**	0.0046**	0.0045**	0.0045**
	(2.12)	(2.06)	(1.99)	(2.24)	(2.17)	(2.12)
$\Delta CEO\_record_{[t-j\ ;\ t]}$	0.0024	0.0043	0.0028	0.0024	0.0043	0.0029
	(0.51)	(1.19)	(0.88)	(0.49)	(1.19)	(0.93)
$\%EMPL\_record_{t-j}$	0.0176**	0.0171**	0.0171**	0.0233***	0.0228***	0.0219***
	(2.06)	(1.99)	(1.97)	(3.08)	(2.99)	(2.85)
$\Delta\%EMPL\_record_{[t-j\ ;\ t]}$	0.0254	0.0162	0.0201*	0.0292*	0.0200*	0.0235**
	(1.63)	(1.32)	(1.80)	(1.89)	(1.68)	(2.18)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
ACC	Ohlson	Ohlson	Ohlson	Ohlson	Ohlson	Ohlson
Firm variables	Yes	Yes	Yes	Yes	Yes	Yes
Person variables	Yes	Yes	Yes	No	No	No
N	99,676	95,327	90,880	99,676	95,327	90,880
Pseudo R sq.	0.2467	0.2464	0.2490	0.2441	0.2438	0.2464
In-sample AUC	0.8978	0.8987	0.9007	0.8966	0.8977	0.8998
πBankrupt	0.0123	0.0116	0.0110	0.0123	0.0116	0.0110

This table conducts a changes-and-levels analysis regarding the CEO having a criminal record and the percentage of employees having criminal records. Specifically, we split the criminal record variables into a level variable at the beginning of the period (*t* -1 in column 1, *t* – 2 in column 2, and *t* – 3 in column 3), and a change variable over the period (*t* – 1 to *t* in column 1, *t* – 2 to *t* in column 2, and *t* – 3 to *t* in column 3). We estimate the regressions applying the Ohlson model with a hazard estimation (Shumway 2001). *CEO_record* indicates that the CEO has a criminal record. Δ*CEO_record* is the change in *CEO_record*. *%EMPL_record* is the percentage of employees with criminal records. Δ*%EMPL_record* is the change in *%EMPL_record*. The control variables, as well as industry and year fixed effects, are estimated but for brevity not reported. Accountig ratios are winsorized at the lower and upper 1% level. The *z*-statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

Table OA8. Long-term bankruptcy prediction

	Reported coefficients: Marginal effects at mean					
	With person-specific controls			Without person-specific controls		
Dependent variable: *Bankrupt*	$t + 1$	$t + 2$	$t + 3$	$t + 1$	$t + 2$	$t + 3$
	(1)	(2)	(3)	(4)	(5)	(6)
CEO_record_t	0.0032	0.0028	0.0031	0.0034^{*}	0.0029	0.0033
	(1.57)	(1.36)	(1.52)	(1.69)	(1.43)	(1.58)
$\%EMPL\_record_t$	0.0092	0.0086	0.0100	0.0147^{**}	0.0134^{*}	0.0137^{*}
	(1.11)	(1.02)	(1.16)	(1.99)	(1.78)	(1.79)
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
ACC	Ohlson	Ohlson	Ohlson	Ohlson	Ohlson	Ohlson
Firm variables	Yes	Yes	Yes	Yes	Yes	Yes
Person variables	Yes	Yes	Yes	No	No	No
N	85,624	75,605	67,437	85,624	75,605	67,437
Pseudo R sq.	0.1385	0.0965	0.0797	0.1360	0.0942	0.0781
In-sample AUC	0.8298	0.7878	0.7642	0.8282	0.7855	0.7622
π*Bankrupt* t + 1/2/3	0.0103	0.0097	0.0095	0.0103	0.0097	0.0095

This table examines whether criminal records of CEOs and employees predict bankruptcies for extended horizons using a modified version of Eq. (1), applying the Ohlson model, and a hazard estimation (Shumway 2001). The Ohlson model variables, *firm variables*, and *person variables* are estimated, as well as industry and year fixed effects, are estimated but for brevity not reported. Accounting ratios are winsorized at the lower and upper 1% level. All variables are defined in Appendix A of the manuscript. The *z*-statistics are in parentheses. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

Table OA9. Propensity-score matching, matched samples descriptive statistics

Panel A: Summary statistics of the matched sample

	Treated (*Bankrupt*=1)	Control (*Bankrupt*=0)			Used for matching?
	Mean	Mean	Diff.	*t*-value	
	(1)	(2)	(3)	(4)	(5)
<u>Prediction model variables and variables of interest</u>					
NWC/TA	0.151	0.150	0.002	(0.16)	Yes
TL/TA	0.908	0.899	0.009	(1.07)	Yes
Log(TA)	9.745	9.700	0.046	(1.20)	Yes
CL/CA	1.236	1.230	0.005	(0.20)	Yes
NI/TA	-0.062	-0.051	-0.011*	(-1.74)	Yes
EBITDA/TL	0.025	0.037	-0.012	(-1.42)	Yes
NITWO	0.661	0.673	-0.013	(-0.65)	Yes
OENEG	0.237	0.228	0.009	(0.53)	Yes
CHIN	-0.218	-0.244	0.026	(0.88)	Yes
SCORE	0.054	0.054	-0.000	(-0.02)	
CEO_record	0.279	0.205	0.074***	(4.26)	No
%EMPL_record	0.214	0.196	0.019***	(3.48)	No
<u>Person variables</u>					
CEO_HighEduc	0.115	0.116	-0.001	(-0.06)	Yes
%EMPL_HighEduc	0.043	0.041	0.002	(0.53)	Yes
CEO_Female	0.051	0.037	0.014*	(1.70)	Yes
%EMPL_Female	0.238	0.227	0.011	(1.26)	Yes
CEO_log(Age)	3.840	3.837	0.003	(0.38)	Yes
%EMPL_log(Age)	3.616	3.620	-0.004	(-0.60)	Yes
CEO_Married	0.788	0.800	-0.012	(-0.71)	Yes
%EMPL_Married	0.432	0.433	-0.001	(-0.11)	Yes
CEO_CorrupIndex	-93.164	-93.166	0.002	(0.01)	Yes
%EMPL_CorrupIndex	-90.624	-90.835	0.212	(0.96)	Yes
<u>Additional firm variables</u>					
EquityFirmOwner/TL	0.098	0.110	-0.012	(-0.78)	Yes
EquityPersOwner/TL	0.017	0.022	-0.004	(-0.65)	Yes
log(Employees)	3.292	3.267	0.025	(1.03)	Yes
StdROA	0.116	0.113	0.003	(0.56)	Yes

Panel B: Bankruptcy likelihood estimation with matched sample

	Dependent variable: *Bankrupt*$_t$ Reported coefficients: Marginal effects at mean
CEO_record$_t$	0.0945***
	(3.73)
%EMPL_record$_t$	0.4484***
	(3.70)
All matching variables from Panel A	Yes
N	2,400
Pseudo R sq.	0.0193
In-sample AUC	0.5933
π*Bankrupt*	0.5000

This table shows the results of using propensity-score matching. Treatment observations (last firm-year observations preceding bankruptcy) are propensity-score matched with firm-year control observations that do not go bankrupt within the following three years. Matches are identified within the same industry-year. We use *SCORE* for propensity-score matching, use 1:1 matching, a caliper of 0.005, and match without replacement. *CEO_record* indicates that the CEO has a criminal record. *SCORE* is the predicted values of a bankruptcy likelihood estimation including the Ohlson model variables, *firm variables*, and *person variables*, excluding the two criminal record variables. *CEO_record* indicates that the CEO has a criminal record. *%EMPL_recond* shows the percentage of employees with criminal records. Panel A displays descriptive statistics of the propensity-score matched sample. The first (second) column shows mean statistics for the treatment (control) observations. Mean differences are presented in column 3, along with *t*-tests for differences in mean in column 4. Column 5 denotes whether a variable is used in the propensity-score matching. Panel B shows the results of a logistic regression using the matched sample. The estimation is a logit regression with firm and year clustered standard errors. *z* statistics are in parentheses. We use all matching variables as controls in the estimation. Accounting ratios are winsorized at the lower and upper 1% level. All variables are defined in Appendix A of the manuscript. ***, **, * represent significance levels at 0.01, 0.05, and 0.10, respectively (two tailed test).

3 Online Appendix C: Danish crime codes and FBI classifications

We map the Danish crime codes into the FBI white-collar and NIBRS categorizations. The conversion tables are based on Appendix F and H in Andersen et al. (2020). We show the conversion tables in Table OA10.

Table OA10. Danish crime codes and FBI classifications

English description	Danish code	White-Collar crime			FBI NIBRS classification			
		Fraud	Legal	Corporate	Person	Property	Society	Other
Forgery	1304	X				X		
Forgery by check	1308	X				X		
Embezzlement	1354	X				X		
Fraud (credit, unemployment etc.)	1357	X				X		
Fraud (checks)	1360	X				X		
Breach of trust (using checks, credit cards, computers)	1363	X				X		
Extortion and usury	1366	X				X		
Debtor fraud	1372	X				X		
Tax fraud	1384	X						X
Serious fraud cases (accounting fraud, etc.)	1398	X				X		
Counterfeiting money and legal evidence	1430	X						X
Breaking tax laws	3610	X						X
Money laundering and related acts	3810	X						X
Legal abuse, confidential breach, court office	1415		X					X
False statement to court	1420		X					X
False statement	1425		X					X
Illegal occupation (gambling, begging, service business)	1450		X					X
Breaches confidentiality, racial discrimination, defamation, etc.	1485		X					X
Health and social legislation	3815			X				X
Housing and construction laws	3820			X				X
Environmental law violations	3825			X				X
Employer violations (driving, hours, wages)	3835			X				X
Corporate laws (competition, marketing, accounting, etc.)	3840			X				X
Assault against public servant while in discharge of his duty	1210				X			
Riot/ disturbance of public order	1220				X			
Attempted homicide	1240				X			
Common assault	1252				X			
Grievous assault	1255				X			
Particularly grievous assault	1258				X			
Domestic violence against innocent	1260				X			
Intentional bodily harm	1270				X			
Intentional bodily injury	1280				X			
Threats	1292				X			
Homicide	1230				X			
Involuntary manslaughter/ bodily harm	1283				X			
Involuntary manslaughter with driving accident	1460				X			
Crimes against life and body (e.g., contribution to suicide, not helping injured)	1286				X			
Crimes against personal freedom (e.g., detention, trafficking)	1289				X			
Incest.	1110				X			
Rape, etc.	1120				X			
Heterosexual sexual offense against child under 12 years	1130				X			
Sexual offense against child under 12 years	1131				X			
Heterosexual offense in general	1140				X			
Sexual crime against child between 13 and 14 years	1141				X			
Sexual crime in general	1145				X			
Homosexual sexual offense against children under 12 years	1150				X			

Table OA10 cont'd

English description	Danish code	White-Collar crime: Fraud	White-Collar crime: Legal	White-Collar crime: Corporate	FBI NIBRS classification: Person	FBI NIBRS classification: Property	FBI NIBRS classification: Society	FBI NIBRS classification: Other
Homosexual sexual offenses in general	1160				X			
Arson	1312					X		
Burglary from location/business	1316					X		
Burglary from house/apt	1320					X		
Burglary from uninhabited buildings	1324					X		
Vandalism	1390					X		
Theft from car, boat, etc.	1328					X		
Store Thefts etc.	1332					X		
Other thefts	1336					X		
Larceny by finding	1351					X		
Theft of registered vehicle	1339					X		
Theft of moped	1342					X		
Theft of bike	1345					X		
Theft of other vehicle	1348					X		
Robbery	1380					X		
Handling stolen goods	1376					X		
Careless handling of stolen goods	1394					X		
Drug trafficking	1435						X	
Drug smuggling	1440						X	
Euphoriants act (narcotics)	3210						X	
Legislation related to gambling, licencing, trade	3855						X	
Prostitution, etc.	1180						X	
The Firearms Act	3410						X	
Unknown criminal types	1000							X
Offenses against decency (by pawing)	1172							X
Offense against public decency (by removing cloths)	1174							X
Offense against public decency (other)	1176							X
Offenses against official authorities	1410							X
General public offenses	1445							X
Family relation offense	1455							X
Privacy infringements, defamation	1475							X
Laws concerning. animals, hunting, etc.	3830							X
Legislation applying to the armed forced	3845							X
Legislation applying to public utilities	3850							X
Special laws, other	3865							X
Unspecified legislation	3870							X

This table shows the mapping of the crime codes used by the Danish Criminal Registry to the FBI of white-collar crime definition and FBI NIBRS classifications from Appendix F and H in Andersen et al. (2020) The FBI NIBRS classes are crime against persons, crime against property, crime against society, and other crimes, abbreviated respectively. X marks the corresponding category.

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