

## Motivation

- Climate-related risks are becoming more and more relevant
  - Transition risks: regulatory reform intended to combat global warming
  - Physical risks: emerge from extreme (weather) events
- Adequate disclosure aids efficient pricing of risks
- Securities and Exchange Commission (SEC) requires firms to report self-identified (climate) risks in their annual 10-K filings (e.g. item 1.A Risk factors)
- We use BERT, a state-of-the-art NLP technique, to develop firm-specific measures of climate risks based on (qualitative) regulatory disclosure
- Analyse effect on term structure of credit default swap (CDS) spreads
  - Climate change affects firms at different horizons → various CDS maturities
  - CDS market unlikely to be driven by preferences, focus on risk (hedging)

## The effect of (climate) risk disclosure on credit spreads: theory

### Risk-perception effect

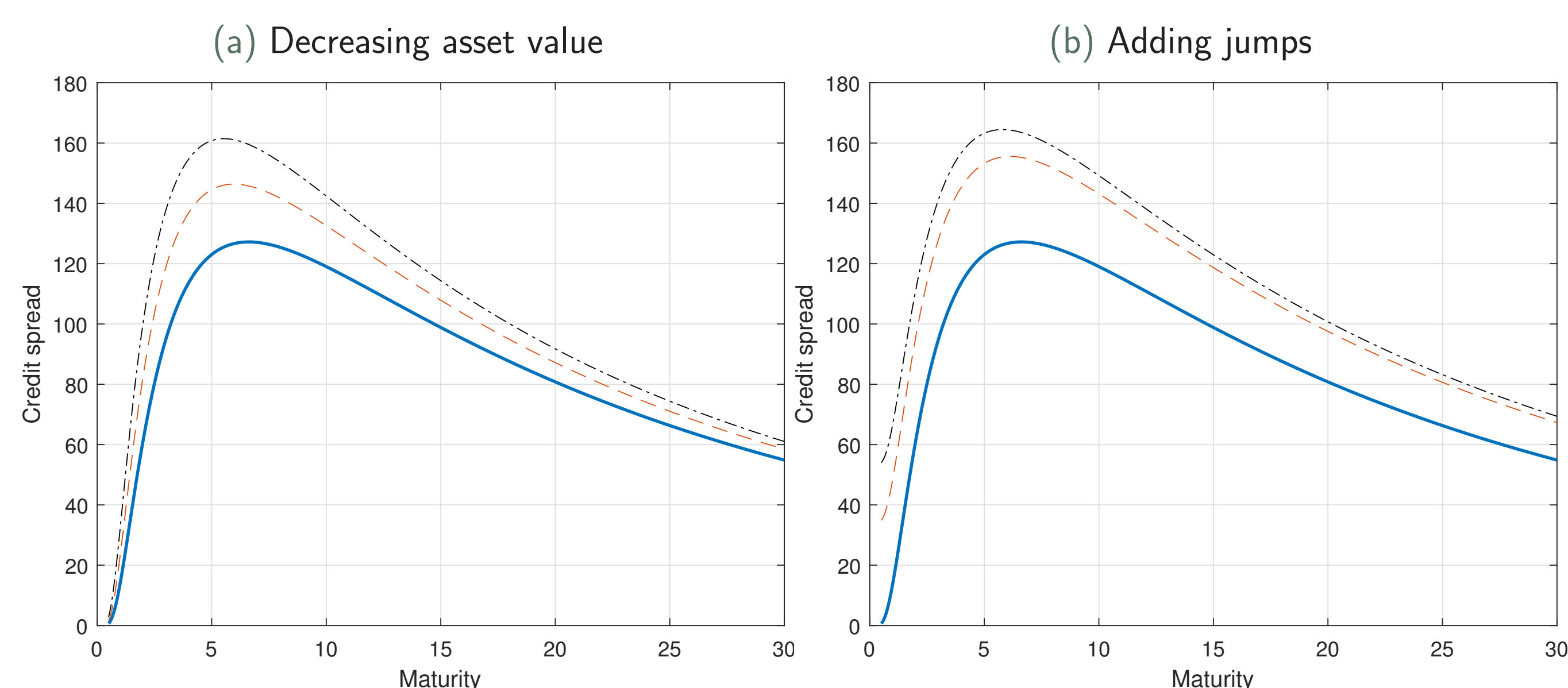
Risk disclosure may increase perception of corporate risk (Kothari et al., 2009)

### Transition risk

- Argument based on the classical Merton (1974) model
- Smooth transition to new regulatory regime will reduce firm's asset value

### Physical risk

- Increase in the severity and frequency of (extreme) climate events
- Adding jumps to model (Zhou, 2001)



### Information uncertainty effect

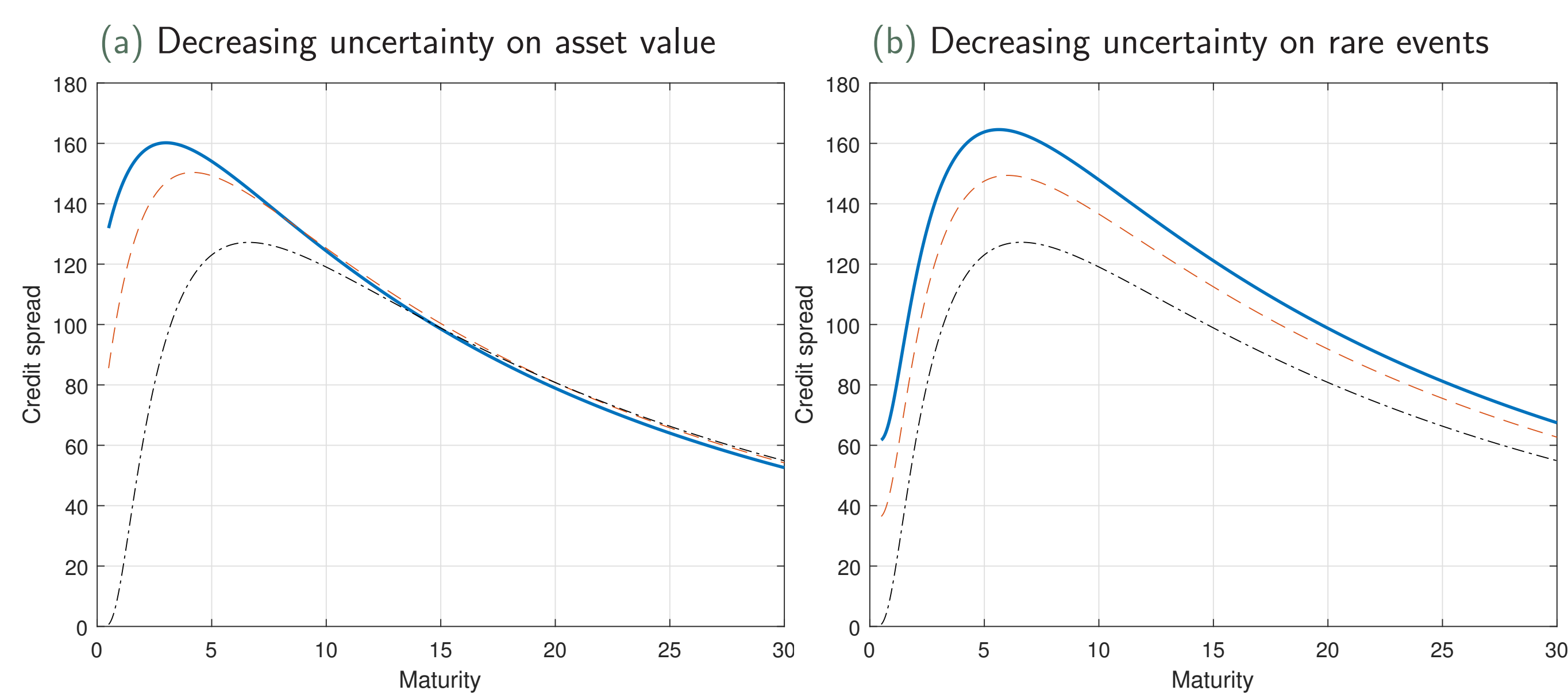
Risk disclosure may reduce information asymmetry between firms and investors

### Transition risk

- Disclosure reduces information uncertainty on firm's asset value (Duffie & Lando, 2001)

### Physical risk

- Argument follows from implications of imprecise knowledge about rare events under ambiguity aversion (Liu et al., 2005)



## Data

- CDS data from Thomson Reuters Datastream
- 10-K filings in SEC's Edgar database
- Period: February 2010 - December 2018
- Firm-specific and macroeconomic controls taken from prior literature (Collin-Dufresne et al., 2001; Ericsson et al., 2009; Han & Zhou, 2015)

## Methodology – Industry classification

Sustainability Accounting Standards Board's (SASB) Sustainable Industry Classification System (SICS)

- Emphasizes a company's sustainability profile
- SASB's materiality map
  - Industry level climate risk materiality (Matsumura et al., 2018)
  - Climate risks (disclosure) only relevant in so-called 'material' industries
  - Different materiality subsamples: general and focus on physical risk
- Industry level clustering of standard errors

## Methodology – BERT

= Bidirectional Encoder Representations from Transformers

- Developed at Google (Devlin et al., 2019)
- Contextual neural language model
- Used on Item 1.A in 10-K reports
  - Look for presence of climate-relevant topics (CN task)
  - Assessment transition or physical risk (TP task)



Table 1: Model performance

Model	CN Task		TP Task	
	Acc	F1	Acc	F1
Baseline	81.07	82.03	58.60	48.60
BERT-Single	94.17	94.07	<b>90.78</b>	<b>90.27</b>
BERT-Multitask	98.06	98.02	85.44	82.36
BERT-GCE	94.17	94.07	90.29	89.68
BERT-Multi-GCE	<b>99.51</b>	<b>99.50</b>	89.81	88.45

- Sentence level (raw) score
- Aggregated on document level (= firm-year level)
- ⇒ *Transition* and *Physical* score

## Methodology – Regression setup

Baseline model - Panel first-difference model

$$\Delta S_{i,t+1}^m = \beta_T \Delta Transition_{i,t} + \beta_P \Delta Physical_{i,t} + \Phi \Delta X_{i,t} + \Theta \Delta Y_t + \epsilon_{i,t+1},$$

with  $S_{i,t+1}^m$  next month's (average)  $m$ -year spread

Paris agreement, December 2015

- Accelerated the global push for climate regulation
  - Especially relevant for transition risk disclosure
  - Effect *Transition* should be even stronger after the Paris agreement
- Introduce post-Paris dummy and interact with *Transition* and *Physical*



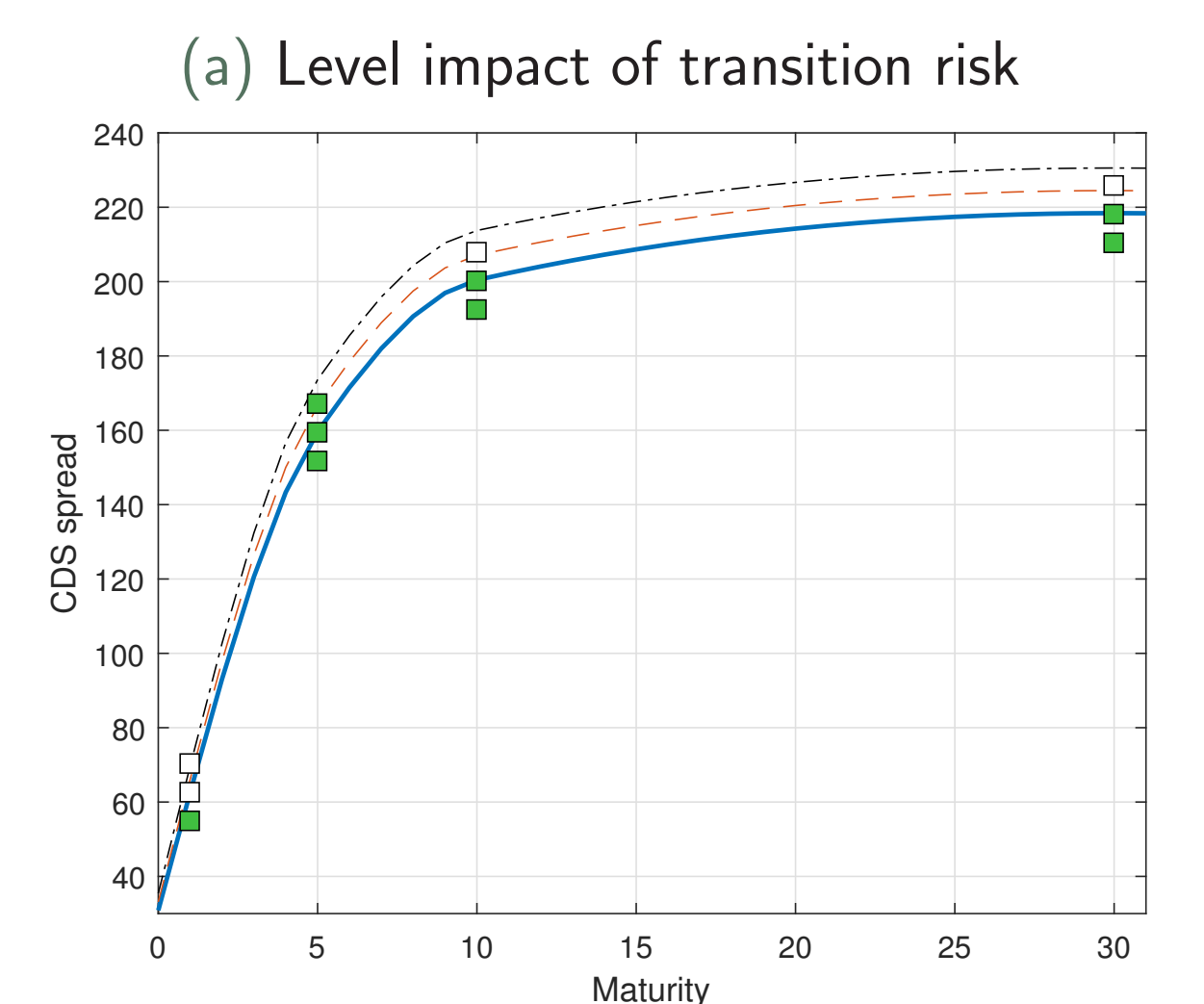
## Main results

General climate material sample

Table 2: Results for subsample of material industries, controlling for the Paris agreement

	$\Delta S^{1Y}$	$\Delta S^{5Y}$	$\Delta S^{10Y}$	$\Delta S^{30Y}$	$\Delta S^{1Y}$	$\Delta S^{5Y}$	$\Delta S^{10Y}$	$\Delta S^{30Y}$
$\Delta Physical$	18.283 (16.381)	29.860 (40.673)	25.538 (19.078)	17.304 (14.276)	23.175 (17.956)	19.490 (13.909)	22.125 (17.660)	20.953 (13.802)
$\Delta Transition$	10.940 (7.618)	-6.376 (13.647)	<b>33.592**</b> (16.656)	0.548 (19.797)	<b>35.364*</b> (18.338)	5.288 (20.791)	<b>32.050*</b> (19.284)	4.723 (21.181)
$\Delta Physical \times Post$		-66.581 (115.552)		12.901 (103.051)		-5.912 (85.884)		-15.442 (81.507)
$\Delta Transition \times Post$		<b>74.968*</b> (43.759)		<b>135.017***</b> (50.174)		<b>123.703**</b> (48.843)		<b>112.892**</b> (43.981)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9972	9972	9972	9972	9972	9972	9972	9972
R-squared	0.028	0.030	0.068	0.076	0.067	0.074	0.062	0.067

S.e. in parentheses. \*, \*\*, and \*\*\* denote p-levels below 10%, 5%, and 1%.



A one-standard-deviation increase in *Transition* leads to an increase of 6.99bps (4.4%) in the average five-year CDS spread for the post-Paris period.

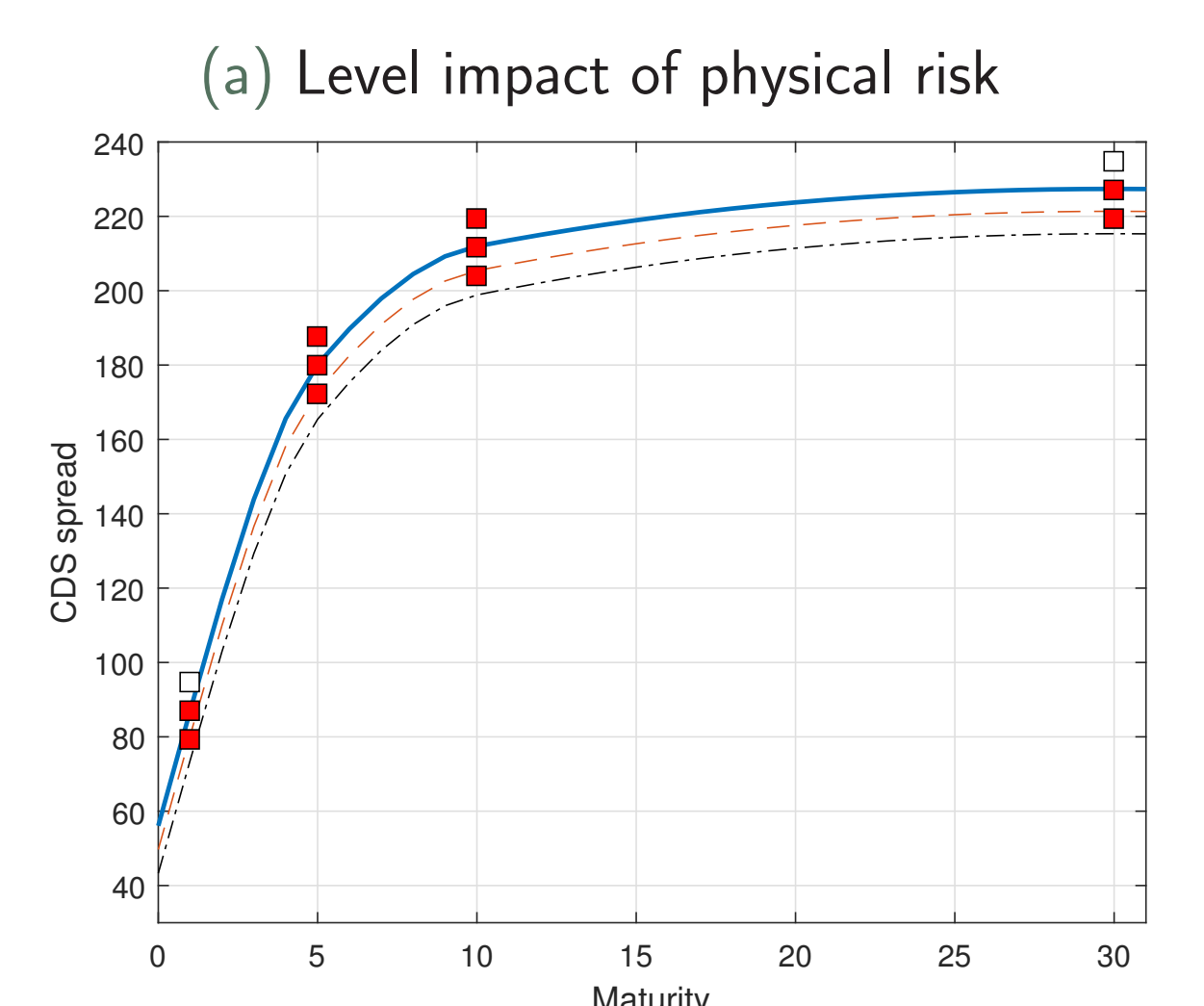
### Focus on physical risk material industries

A one-standard-deviation increase in *Physical* results in a decrease in the average five-year CDS spread of 7.37bps (-4.1%).

Table 3: Results for subsample of physical material industries

	$\Delta S^{1Y}$	$\Delta S^{5Y}$	$\Delta S^{10Y}$	$\Delta S^{30Y}$
$\Delta Physical$	-379.924** (178.394)	-419.190** (134.813)	-372.812** (128.073)	-342.756** (138.702)
$\Delta Transition$	168.027* (78.750)	198.936** (59.814)	183.583** (45.513)	168.935** (43.728)
Controls	Yes	Yes	Yes	Yes
N	6971	6971	6971	6971
R-squared	0.028	0.030	0.068	0.076

S.e. in parentheses. \*, \*\*, and \*\*\* denote p-levels below 10%, 5%, and 1%.



## Robustness check – Substantial advantage new BERT measure?

- Carbon emissions data as proxy for transition risk
  - Comparing with keyword-based NLP algorithms
    - CookESG research/CERES climate risk measure based on 10-K reports (Berkman et al., 2019)
    - Scores from Sautner et al. (2020), based on textual analysis of earnings conference calls
- ⇒ BERT measures provide most consistent results in our CDS context

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