The Aggregate Consequences of Default Risk: Evidence from Firm-level Data

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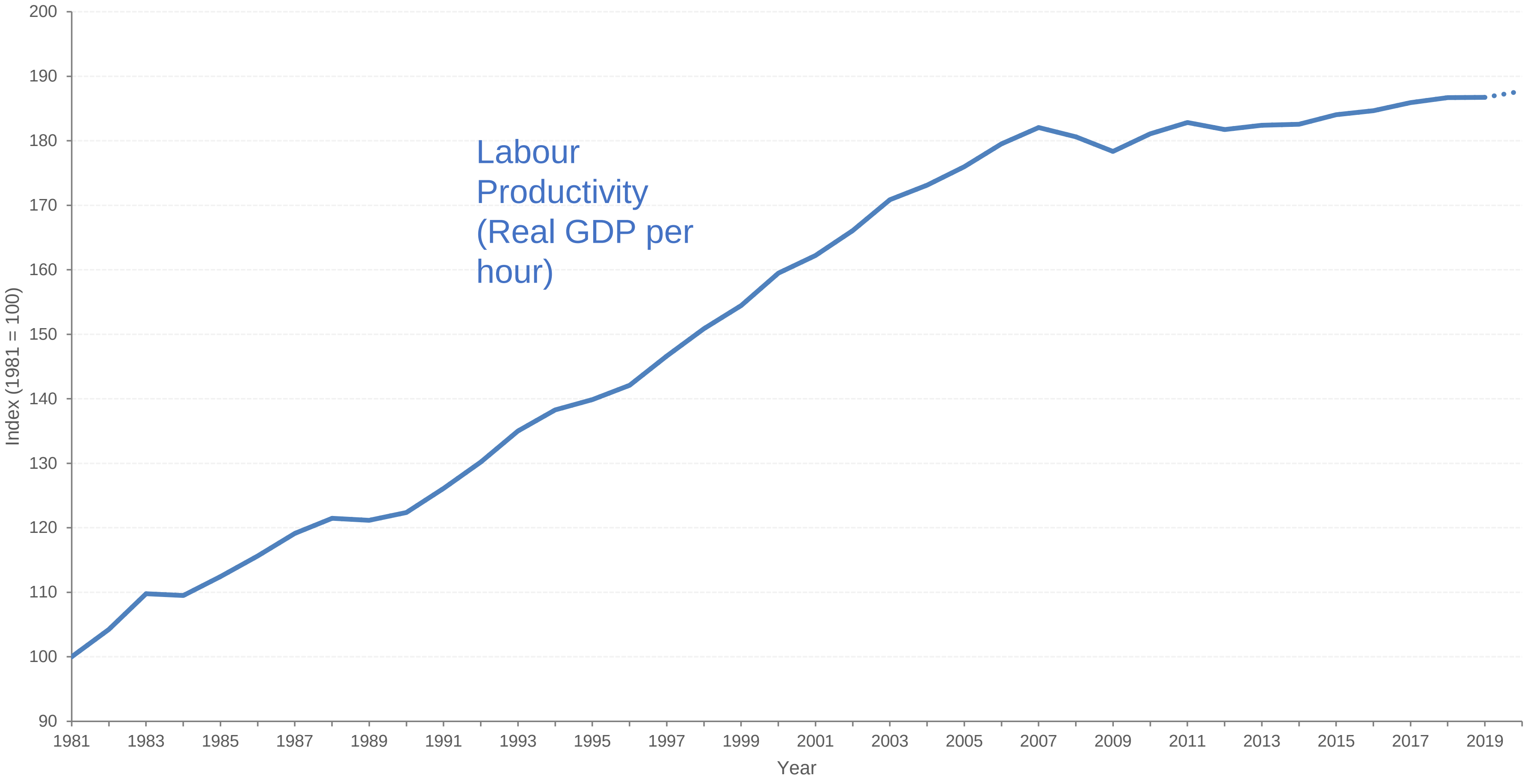
Programme on Innovation and Diffusion

Motivation

- Global Financial Crisis (GFC) heightened interest in the role of financial factors in shaping economic performance.
  - COVID pandemic led to significant government intervention to support firm finances

- How much was the weak productivity growth during and after GFC due to credit market frictions?

UK interesting case: High dependency on bank finance (esp. SMEs) & dramatic productivity slowdown



Source: ONS and OECD data (Teichgraeber and Van Reenen, 2021)

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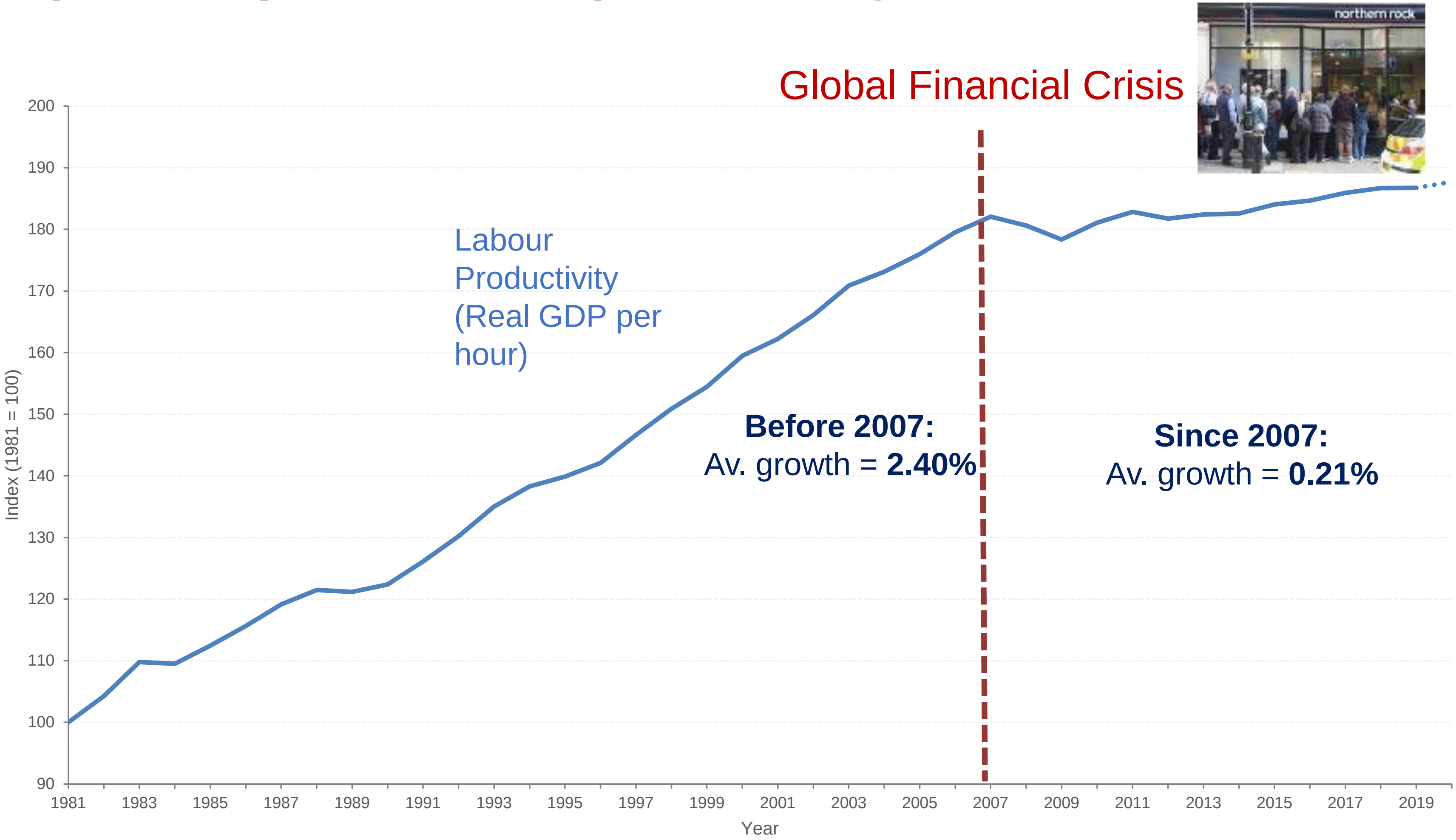
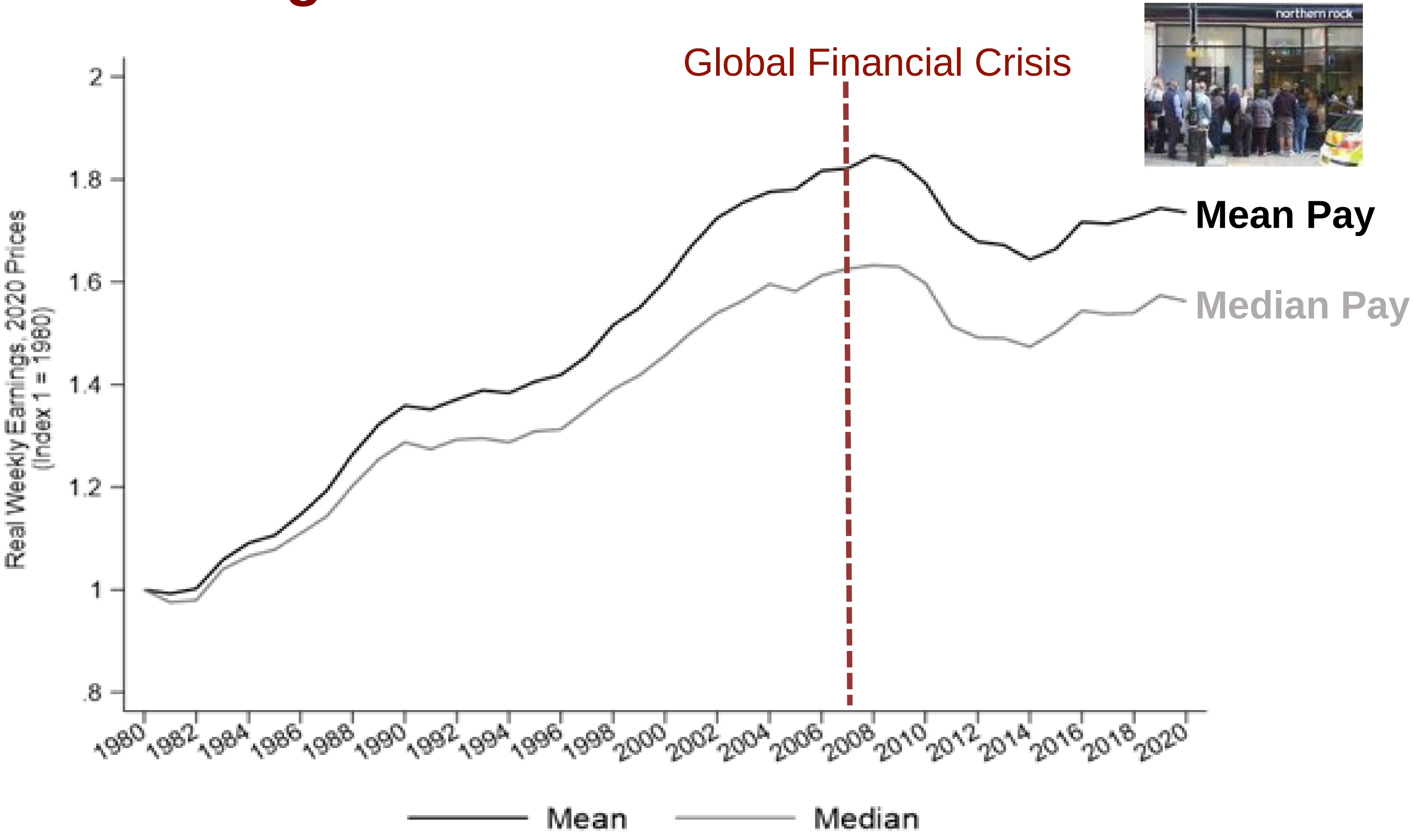


Source: ONS and OECD data (Teichgraeber and Van Reenen, 2021)

Mean and Median individual Wages have also both stagnated since Financial Crisis



Notes: ASHE data

Motivation

- To make progress on this issue, need specific data on how credit frictions affect firms
  - Use Standard & Poor's **Probability of Default (PD) model**

- Take into account firm differences: heterogeneous allocation of credit matters (e.g. Large firms vs. Small and Medium sized Enterprises, SMEs)

- Lessons for COVID Pandemic & aftermath. Lack of access of credit to SMEs major factor in holding down output.

Our Key Contributions

- Develop model with **equilibrium default -** motivates use of default risk as a measure of firm-level credit frictions
- Tractable framework to quantify productivity losses from credit frictions with minimal data requirement (basically, firm-specific default risk and employment)
- Apply framework to rich dataset matching default risk with administrative data on jobs (+ investment, productivity, etc.)
- Use private sector population (not just manufacturing) & entire size distribution of firms

Our Key Results

- Credit frictions depress output – annual average loss of **~28% of GDP (**2005-2013)
- Credit frictions explain about **half** of the productivity drop in the Global Financial Crisis 2008-09
- Losses driven primarily by lower **aggregate capital** (“scale”) not misallocation of credit across heterogeneous firms (“TFP”)
- Output losses (in levels and changes) are <u>much</u> larger for SMEs than large firms
- Current work extending to 2013-2018 period backs this up (& finds more negative effects in Brexit period)

Related Literature

- **Impact of Great Recession via financial frictions:** Chodorow-Reich (2014); Huber (2018); Greenstone et al (2020); Bentolila et al (2015); Schivardi et al (2018); Anderson et al (2019); de Ridder (2019)
- **Macro-economic effects of credit frictions:** Midrigan & Xu (2014); Aghion et al (2012, 2014); Moll (2014); Asker et al (2014); **Gilchrist et al** (2013); Jeong and Townsend (2007); Amaral and Quintin (2010); Buera and Shin (2013); Catherine et al (2018); Anderson et al (2019)
- **Misallocation literature:** Restuccia & Rogerson (2008); **Hsieh & Klenow** (2009, 2014); Bartelsman et al (2013); Asker et al (2014); Hopenhayn (2012,2014); Baqaee and Fahri (2019, 2020)
- **Causes of the productivity slowdown: Gopinath et al** (2017); Syverson (2017); Gordon (2016); Brynjolfsson et al (2017); Bloom, Jones, Van Reenen & Webb (2020)

Theoretical Framework

Data and Measurement

Core Results

Extensions

Basic Theory

- **Output** for firm *n* in year *t*, $Y_{nt} = \theta_{nt}(L_{nt}^{1-\alpha} K_{nt}^{\alpha})^{\eta}$, $\eta < 1$
- **Firm Profits:** $Y_{nt} - \left(\frac{w_t}{\tau_{nt}^L}\right) L_{nt} - \left(\frac{\rho_t + \delta}{\tau_{nt}^K}\right) K_{nt}$

  Distortions: $\tau_{nt}^L \leq 1, \tau_{nt}^K \leq 1$

  w_t = wage; $\rho_t + \delta$ = cost of capital;

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- **FOC for *L* and *K* imply:**

$$\boldsymbol{Y_{nt} = \theta_{nt}^{\frac{1}{1-\eta}}\psi(w_t\ ,\rho_t + \delta)\tau_{nt}}$$

Where $\boldsymbol{\tau_{nt}} = (\tau_{nt}^L)^{\frac{(1-\alpha)\eta}{1-\eta}}(\tau_{nt}^K)^{\frac{\alpha\eta}{1-\eta}}$; $\psi(.) = \left(\frac{(1-\alpha)\eta}{w_t}\right)^{\frac{(1-\alpha)\eta}{1-\eta}}\left(\frac{\alpha\eta}{\rho_t+\delta_t}\right)^{\frac{\alpha\eta}{1-\eta}}$

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- In frictionless world $\tau_{nt}^{L} = \tau_{nt}^{K} = 1$ for all firms, so output solely determined by fundamental productivity θ_{nt}, technology parameters $(\alpha\ ,\eta, \delta)$ and macro factor prices $(w_t\ ,\rho_t)$

Aggregate losses from market frictions

- **Aggregate Output,**

$$
\begin{aligned}
Y_t &= \sum_{n=1}^{N} Y_{nt} \\
&= \underbrace{\psi\left(w_t\ , \rho_t + \delta\right)}_{\text{Factor prices}} \underbrace{\left(\sum_{n=1}^{N} \theta_{nt}^{\frac{1}{1-\eta}}\right)}_{\text{Productivity}} \underbrace{\Theta_t}_{\text{Distortions}}
\end{aligned}
$$

where our aggregate measure of distortions is:

$$\Theta_t = \sum_{n=1}^{N} (\omega_{nt}\, \tau_{nt})$$

with productivity weights: $\omega_{nt} = \theta_{nt}^{\frac{1}{1-\eta}} / \sum_{n=1}^{N} (\theta_{nt}^{\frac{1}{1-\eta}})$

What reference benchmark?

- For any **reference** level of output $\widehat{Y_t}$, we can calculate the output loss as:

$$\frac{\widehat{Y_t}-Y_t}{\widehat{Y_t}} = 1 - \left[\frac{\Theta_t}{\widehat{\Theta_t}}\right]^{\frac{1-\eta}{1-\alpha\eta}}$$

- **Benchmark I:** No credit frictions (τ_{nt}^{K} = 1)
- **Benchmark II:** Changes over time. How much of empirical change in productivity is due to distortions?

What reference benchmark?

- For any **reference** level of output $\widehat{\boldsymbol{\Theta}_t}$ we can therefore calculate the output loss as:

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- **Benchmark I:** No credit frictions (τ_{nt}^{K} = 1)
- **Benchmark II:** Changes over time. How much of empirical change in productivity is due to distortions?
- **Benchmark II: S**et counterfactual default rate equal to that of the lowest firm (or say 5th percentile) in the industry
  - (Equilibrium with fully observable & contractable managerial effort (no moral hazard) and non-zero default)

Model based measure of credit frictions (τ^K_{nt})

- Simple model of equilibrium credit contracts (Innes, 1990 & Besley et al, 2012) with moral hazard (unobserved costly managerial effort) micro-founds a measurable proxy for τ^K_{nt}

Timing of Lending Contracts

1. Nature assigns each firm to a bank
2. Banks offer credit contracts ***{B,R} B = borrowing, R = repayment,*** given a firm's outside option (switching cost of moving to another bank)
3. Firm chooses effort given costs of effort function ***c(ϕ***)
4. Default occurs with probability ***1 - ϕ***
5. If there is no default, firms make hiring decisions, produce and repay loans

Solve by backward induction (abstract from labor distortion for now)

Model based measure of credit frictions (τ_{nt}^{K})

Model implies that **repayment probability (ϕ)** allows us to calculate firm level **capital distortion (τ_{nt}^{K})**:

$$\tau_{nt}^{K} = \hat{\tau}(\delta, \rho_t, \phi_{nt}) = \left[1 + \frac{(1+\rho_t)\left(1-\phi(A,\theta)_{nt}\right)}{(\delta+\rho_t)\phi(A,\theta)_{nt}}\right]^{-1} \leq 1$$

Where $\phi(A,\theta)$ is increasing in collateral (*A*) and productivity (θ); ρ_t = interbank interest rate; δ = capital depreciation rate

τ_{nt}^{K} a simple increasing function of ϕ (e.g. if ϕ=1 then τ_{nt}^{K}=1)

Theoretical Framework

Data and Measurement

Core Results

Extensions

Data set

- Unique data set which matches:
  - **time-varying firm-specific measure of credit frictions** (repayment probability, ϕ_{nt}) with
  - Census Bureau (ONS) **administrative panel data** on employment [& value added, investment in subsample]

Data set

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  - Census Bureau (ONS) **administrative panel data** on employment [& value added, investment in subsample]

- Estimate repayment probabilities using credit scoring model (S&P's "PD Model"):
  - **Inputs:** all UK public & private company accounts from BvD ORBIS/FAME, industry & macro factors
  - **Output:** risk score (AAA, BBB, etc.) and continuous **P**robability of **D**efault (=1 – Repayment Probability)
  - Use PDs to capture information set of lenders at time of lending decision
  - These scores widely used for lending decisions

Matching Data

- Generate default rates from S&P PD model applied to population of company accounts (private and public firms)
  - PD model just needs 4 key items which almost all firms provide (fixed & total assets; current & total liabilities). Uses many other accounting items (if available)
  - Obtain 15.8 million PDs from 16.6 million possible firm-year observations

Measurement of firm level relative productivity (ω_{nt})

- **Relative Productivity =** $\omega_{nt} = \frac{\gamma_{nt}}{\hat{\tau}_{nt}^{\alpha\eta/(1-\eta)}} \Theta_t$

γ_{nt} is firm *n*'s employment share

$\hat{\tau}_{nt}$ is a function of observed PDs, ϕ

$$\Theta_t = \left[\sum_{n=1}^{N} \left(\frac{\gamma_{nt}}{\hat{\tau}_{nt}^{\alpha\eta/(1-\eta)}} \right) \right]^{-1} \leq 1$$

Note:

- In absence of distortions, relative TFPQ equals firm employment share: $\omega_{nt} = \gamma_{nt}$ and Θ_t = 1
- As robustness, we compare to standard TFP measures for subsample where we observe capital stocks

Merging datasets

- Match these 15.8 million observations from ORBIS into ONS Inter-Departmental Business Register (IDBR)
  - Company registration number ("ENTREF") by year. Check against name; address; industry; size
  - **IDBR** has employment, location and industry of all establishments belonging to the firm
  - **In extensions, use ABI/ABS:** stratified random sub-sample of IDBR which has productivity data: output, intermediate goods & services, investment, value added, wage bill, etc.
    - Covers all sectors (not just manufacturing like ASM)

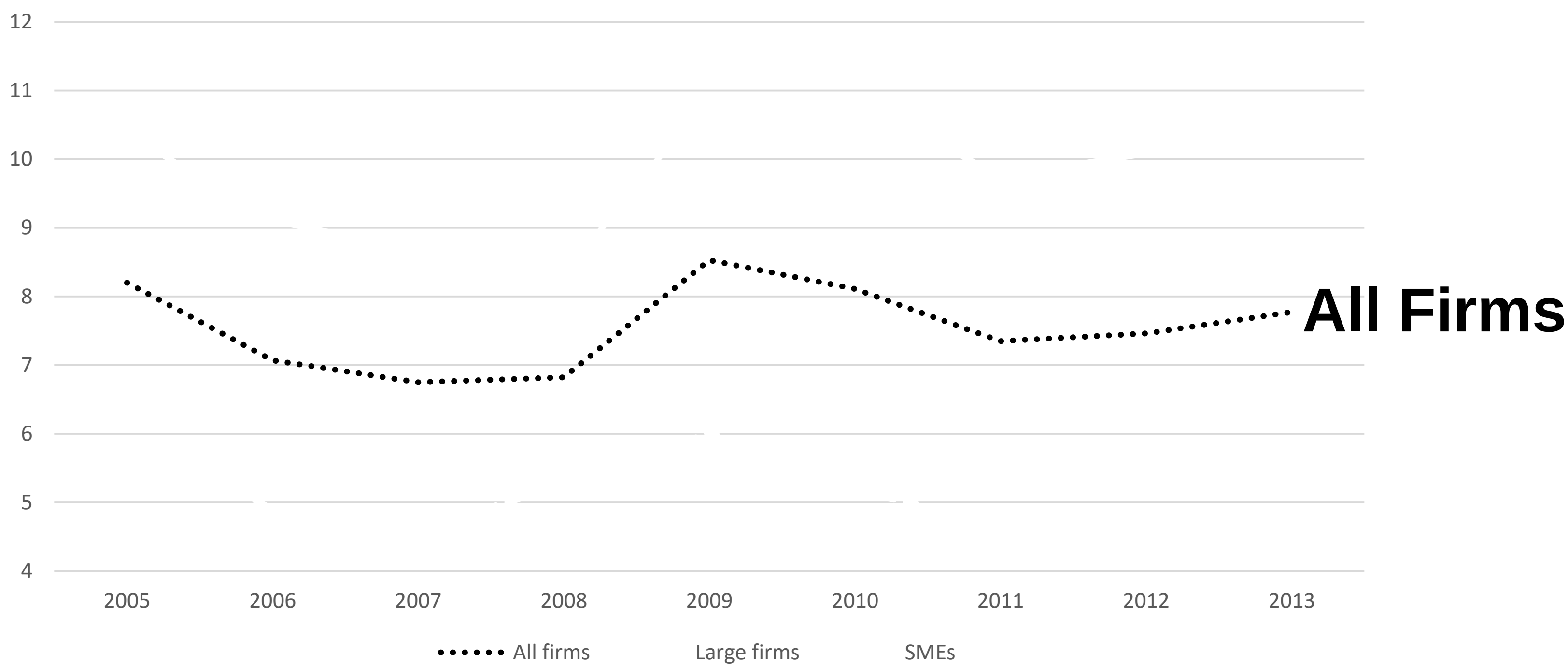
Data set (ORBIS/IDBR match)

- Covers entire non-financial private sector
  - Entire Size distribution; Publicly and privately listed firms

	Total employment	Total Number of firms	# SMEs (under 250 workers)	# large (over 250 workers)	Large firm as % of total jobs
2005	15,604,279	1,377,733	1,371,906	5,827	48.67
2006	15,661,572	1,414,221	1,408,569	5,652	48.48
2007	15,469,375	1,460,639	1,455,388	5,251	48.12
2008	16,211,576	1,545,919	1,540,225	5,694	48.18
2009	15,929,213	1,480,481	1,474,989	5,492	48.78
2010	15,328,929	1,459,680	1,454,545	5,135	48.10
2011	15,469,622	1,502,427	1,497,247	5,180	47.92
2012	15,731,791	1,502,665	1,497,445	5,220	47.74
2013	16,040,370	1,569,340	1,564,028	5,312	47.52

Default probabilities

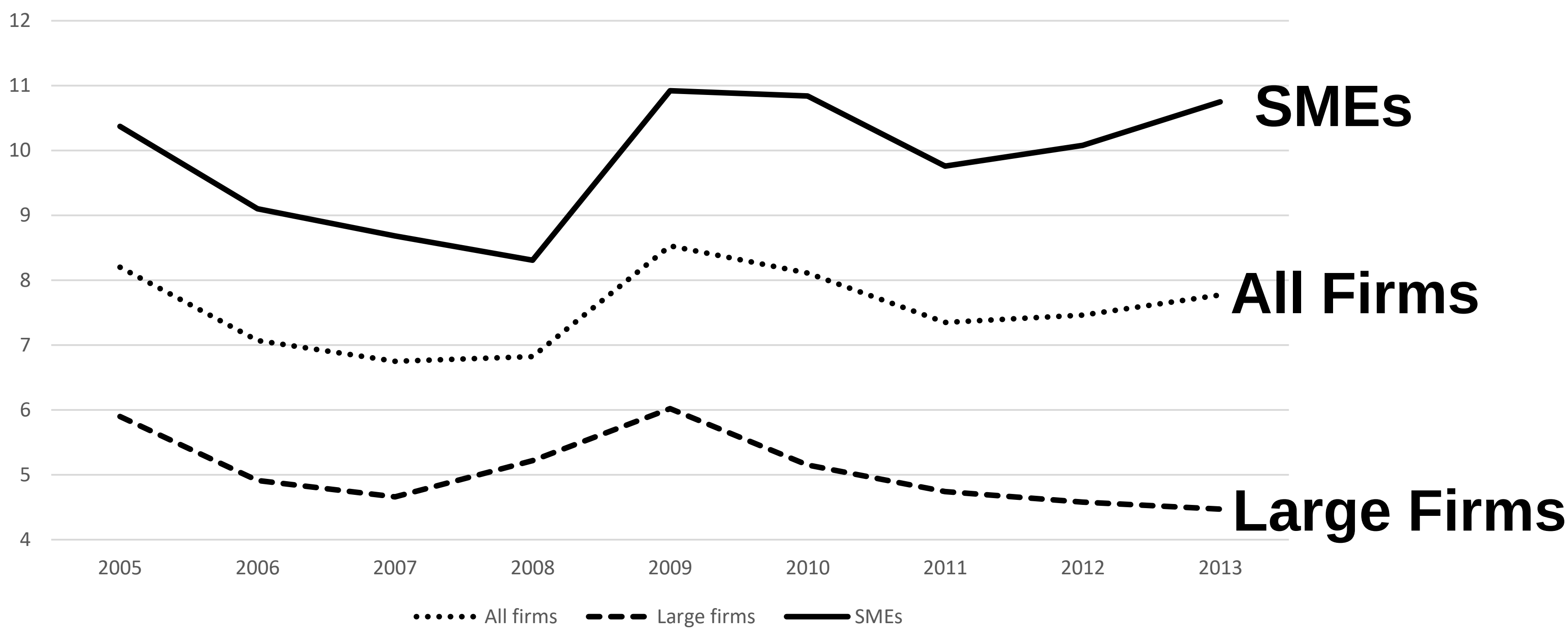
Figure 1: Aggregate probability of default (in %) at one year horizon



- Significant increase in default probability after Global Financial Crisis
- Goes down in recovery but remains higher than pre-crisis,

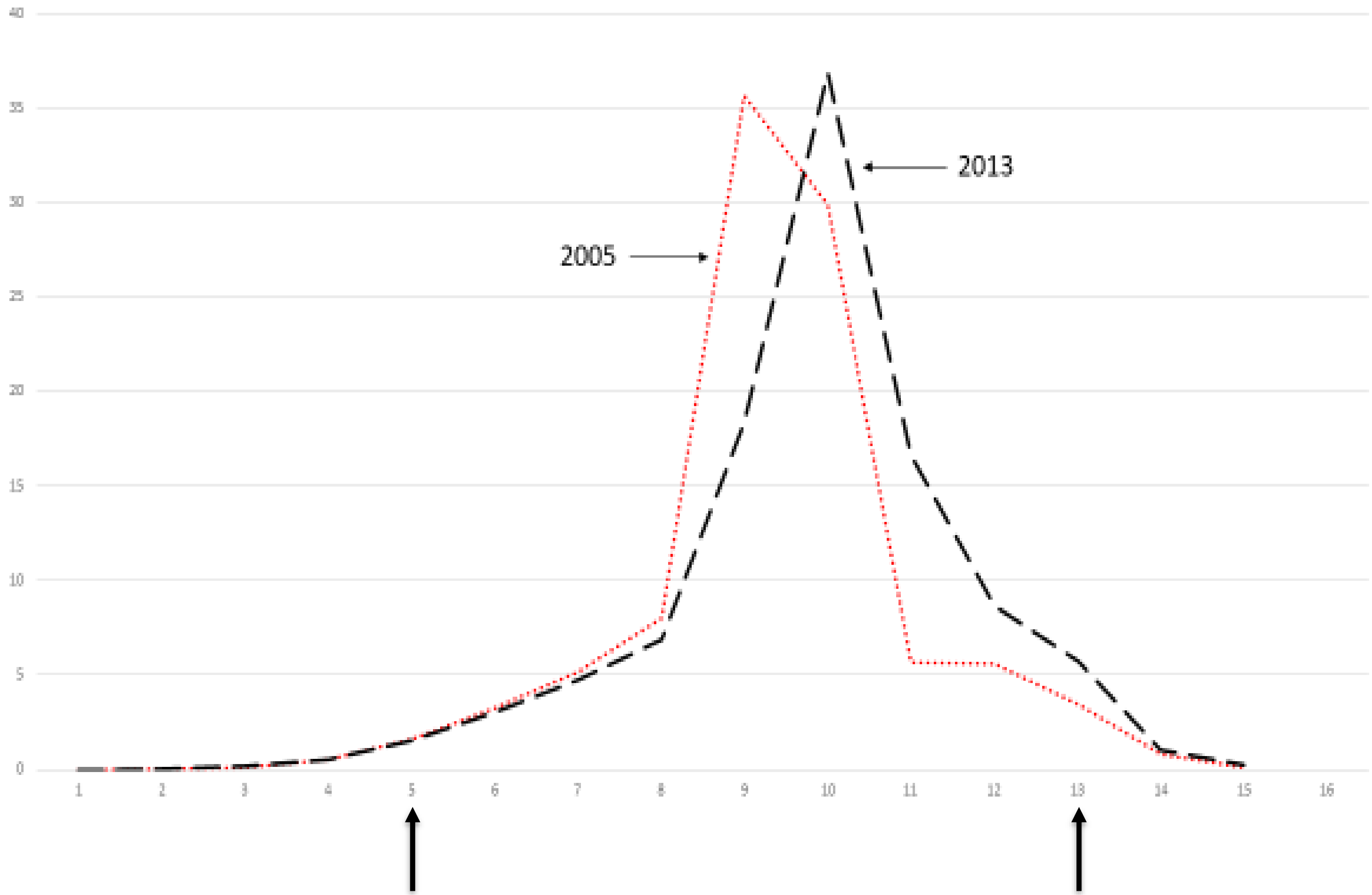
Default probabilities

Figure 1: Aggregate probability of default (in %) at one year horizon by firm size



- Probability of default systematically larger for SMEs
- Whereas large firms fully recovered by 2013, default probabilities remain high for SMEs

Deterioration of risk scores: shift in density to the right (Figure 2)



Risk Score 5 (“BB+”): Default probability 0.5%

Risk Score 13 (“CCC-”): Default probability 36.4%

Theoretical Framework

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Core Results

- **Micro validation of credit friction measure**
- Macro-economic implications
- SMEs vs. Large firms
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Validation of the predictive power of S&P default probability: regress firm outcomes on lagged PDs

Firm Outcomes: employment, value added, survival, capital, investment, etc.

$$\ln(y_{nt}) = \beta \ln \phi_{nt-1} + a_n + a_t + \varepsilon_{nt}$$

Repayment probability

Firm or industry dummies

Time dummies

Various samples/datasources: IDBR; ABI/ABS; ORBIS

Firm performance is increasing in lagged repayment probability (Table 2)

PANEL A: Controls for industry and year fixed effects

	(1) Ln(employment)	(2) Ln(employment)	(3) Ln(vale added)	(4) Ln(capital stock)	(5) Ln(investment)	(6) Ln(total assets)	(7) Ln(fixed assets)	(8) Ln(capital/labor)	(9) Ln(investment/labor)	(10) Ln(investment/capital)	(11) Survival
Ln(Repayment prob)	0.390***	1.680***	2.445***	2.540***	2.535***	3.733***	4.542***	0.360***	1.062***	0.586***	0.045***
	(0.004)	(0.044)	(0.057)	(0.072)	(0.096)	(0.062)	(0.075)	(0.041)	(0.058)	(0.049)	(0.001)
Data	IDBR	ABI/ABS	ABI/ABS	ABI/ABS	ABI/ABS	ORBIS	ORBIS	ABI/ABS	ABI/ABS	ABI/ABS	IDBR
Observations	10,194,209	271,038	254,366	204,951	110,274	195,010	179,796	204,951	110,274	100,650	4,845,158

PANEL B: Controls for industry, year, and firm fixed effects

	(1) Ln(employment)	(2) Ln(employment)	(3) Ln(vale added)	(4) Ln(capital stock)	(5) Ln(investment)	(6) Ln(total assets)	(7) Ln(fixed assets)	(8) Ln(capital/labor)	(9) Ln(investment/labor)	(10) Ln(investment/capital)	(11) Survival
Ln(Repayment prob)	0.007***	0.034**	0.352***	0.076***	0.712***	0.277***	0.369***	0.043**	0.687***	0.664***	0.004***
	(0.002)	(0.015)	(0.034)	(0.019)	(0.069)	(0.038)	(0.038)	(0.022)	(0.068)	(0.063)	(0.001)
Data	IDBR	ABI/ABS	ABI/ABS	ABI/ABS	ABI/ABS	ORBIS	ORBIS	ABI/ABS	ABI/ABS	ABI/ABS	IDBR
Observations	9,716,577	119,691	114,883	117,420	71,329	99,149	96,138	117,420	71,329	71,231	4,597,208

Note: OLS; SE clustered by firm; * 1%, ** 5% * 10% level. Repayment probability at the one-year horizon estimated using data at *t-1*. Years: 2005 to 2013. Industry and year dummies are included in all models.**

Validation of repayment probability as proxy for credit frictions (Table 2B)

- Lagged repayment probabilities significantly & positively correlated with firm performance
- Non-trivial coefficients; e.g. 10% increase in repayment probability associated with 7% increase in investment

Dep. variable:	**Ln(Employment)**	**Ln(Employment)**	**Ln(Value added)**	**Ln(Capital stock)**	**Ln(Investment)**	**Ln(Capital/labor)**	**Ln(Investment/ capital)**	**Survival**
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Further validation of predictive power of Repayment Probability

1. Regression Discontinuity Design around cut-offs
2. Using bank-firm relationships pre-crisis as a natural experiment
3. Use changes to PD algorithm over time

- All suggest that S&P PD data is useful

Theoretical Framework

Data and Measurement

Core Results

- Micro validation of credit friction measure
- **Macro-economic implications**
- SMEs vs. Large firms
- Misallocation vs. scale

Calibration values

Object	Mnemonic	Baseline value	Sensitivity Tests	Source
Elasticity of Output wrt capital	α	0.33	[0.25,0.41] Industry specific shares	Labor share of GDP
Returns to Scale	η	0.85	[0.75, 0.95]	Garicano et al (2016) survey
Capital depreciation	δ	0.05	0.10	Hsieh and Klenow (2009)
Cost of funds	ρ	0.05	Time varying base rate	Hsieh and Klenow (2009)

Aggregate implications: Core Tab 3 results

	Observations	Θ_t	Percentage loss of output	Growth contribution
2005	1,377,733	0.211	27.731	
2006	1,414,221	0.230	26.363	1.875
2007	1,460,639	0.236	25.989	0.507
2008	1,545,919	0.242	25.632	0.481
2009	1,480,481	0.192	29.102	$\boxed{-4.779}$
2010	1,459,680	0.201	28.412	0.969
2011	1,502,427	0.203	28.300	0.156
2012	1,502,665	0.204	28.197	0.144
2013	1,569,340	0.205	28.151	0.063
Average	***1,479,234***	***0.214***	$\boxed{\textbf{\textit{27.542}}}$	

- 27.5% average output loss per annum 2005-2013
- Big loss in 2008-09 Great Recession: accounts for **half of overall productivity fall in this period**
- Continued problems even at end of period

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Aggregate implications: SMEs suffer more than large firms (Table 4)

	SMEs		LARGE FIRMS	
	Theta Θ_t	**% loss of output**	**Theta** Θ_t	**% loss of output**
2005	0.155	32.159	0.319	21.220
2006	0.170	30.847	0.354	19.477
2007	0.176	30.400	0.357	19.317
2008	0.180	30.030	0.354	19.445
2009	0.132	34.471	0.316	21.329
2010	0.132	34.451	0.351	19.598
2011	0.147	32.912	0.322	21.060
2012	0.138	33.824	0.345	19.879
2013	0.130	34.639	0.364	19.000
Average	***0.151***	***32.6%***	***0.343***	***20%***

- Large firms productivity loss is ~fifth vs. ~third for SMES
- Large firms basically fully recovered after crisis whereas SMEs did not.

Theoretical Framework

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Scale effects vs. Misallocation

- **Output losses can be decomposed into two parts**

- **Scale effect:** impact of credit frictions on output through the aggregate stock of capital and labor inputs, holding the joint distribution of frictions and productivity constant

- **Misallocation effect ("TFP"):** impact of credit frictions on output holding both the aggregate stock of capital and labor fixed (depresses aggregate TFP)
  - Captures **how frictions vary with the relative fundamental productivity** of firms
  - Efficiency = channeling inputs to most productive firms

Aggregate losses are due to lower scale of capital not misallocation (Table 3)

	Observations	**Overall** (% loss of output)	**Scale** (% loss of output)	**TFP** (% loss of output)
2005	1,377,733	27.731	25.924	1.807
2006	1,414,221	26.363	24.520	1.843
2007	1,460,639	25.989	24.126	1.863
2008	1,545,919	25.632	23.811	1.821
2009	1,480,481	29.102	27.028	2.074
2010	1,459,680	28.412	26.380	2.032
2011	1,502,427	28.300	26.042	2.259
2012	1,502,665	28.197	25.970	2.227
2013	1,569,340	28.151	25.969	2.183
Average	***1,479,234***	***27.542***	***25.530***	***2.012***

Comparison with “conventional method”

- **Conventional measure of credit market distortions**
- Recover “wedges" from data on capital and output:

$$\boldsymbol{\tau_{nt}^{K}} = \frac{\boldsymbol{(\rho+\delta)K_{nt}}}{\boldsymbol{\alpha\eta Y_{nt}}}$$

- **Pros:**
  - Wider range of distortions, e.g. adjustment costs, capital taxes and subsidies
  - Not subject to measurement error in default risk: lenders could use other unobservable information

- **Cons:**
  - All of measurement error in capital is attributed to factor market distortions. Capital measurement error serious problem, e.g. White et al (2018) on Hsieh-Klenow
  - Cannot relate numbers to specific frictions: “black box"

Table 5: Our method finds losses less than half the size of "conventional method" using MRP variance

	Obs	Our method % loss	"Conventional" % loss
2005	8,295	27.393	56.253
2006	7,533	25.768	59.429
2007	8,159	24.738	62.907
2008	4,987	25.317	66.613
2009	4,907	27.374	69.213
2010	5,306	25.753	67.574
2011	4,975	24.598	65.764
2012	5,086	25.933	67.104
2013	4,801	25.849	65.303
Average	***6,005***	***25.9%***	***64.5%***

Note: ABI/ABS data on manufacturing only (to be consistent with existing literature and capital better measured in this sector)

Robustness and Extensions

- **Incorporating labor market distortions**
- Alternative calibration values
- Using Solow residuals to measure productivity
- Dropping imputed default probabilities
- Using Expected output (instead of actual ex post output)

Incorporating labor market frictions (Table A5): ABI/ABS sample (23% vs 27% in baseline)

	Observations	% loss of output
2005	27,392	26.440
2006	23,749	25.085
2007	26,085	21.229
2008	24,361	22.910
2009	24,260	22.942
2010	24,259	22.870
2011	24,039	18.846
2012	24,646	22.347
2013	23,637	24.154
Average	***24,714***	***23%***

Note: In ABI/ABS output loss is **27%** in baseline. This only considers gain from removing capital market distortions

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Changing Economies of Scale and Output Elasticity (Tab A6)

η / α	0.75	0.77	0.79	0.81	0.83	0.85	0.87	0.89	0.91	0.93	0.95
0.25	13.420	14.098	14.857	15.727	16.753	18.009	19.620	21.800	24.919	29.530	35.662
0.27	14.855	15.635	16.512	17.523	18.722	20.197	22.094	24.656	28.268	33.428	39.349
0.29	16.354	17.244	18.250	19.414	20.801	22.515	24.719	27.680	31.779	37.409	42.641
0.31	17.919	18.927	20.072	21.403	22.994	24.963	27.494	30.862	35.427	41.411	45.521
0.33	19.550	20.686	21.981	23.491	25.301	$\boxed{27.542}$	30.411	34.184	39.179	45.365	48.068
0.35	21.250	22.523	23.978	25.679	27.721	30.247	33.462	37.629	43.004	49.196	50.390
0.37	23.020	24.439	26.064	27.968	30.255	33.075	36.635	41.175	46.865	52.832	52.576
0.39	24.861	26.435	28.241	30.358	32.898	36.018	39.916	44.798	50.722	56.215	54.680
0.41	26.775	28.512	30.507	32.846	35.647	39.067	43.289	48.473	54.533	59.316	56.735

Output losses increasing in importance of capital (**α**) and also in closeness to CRTS (**η = 1**)

More alternative calibration values

- Use SIC3 industry specific factor shares to measure output elasticities (Table A7). **25% average output loss**

- Measure a time-varying frictionless cost of funds (**ρ**) as Central Bank rate + average CDS premium of 6 largest UK banks. **30% average output loss**

- Double depreciation rate to 10% (Table A8). **21% output loss**

Robustness and Extensions

- Incorporating labor market distortions
- Alternative calibration values
- **Using Solow residuals to measure productivity**
- Dropping imputed default probabilities
- Using Expected output (instead of actual ex post output)

Using Solow residuals to measure productivity (Table A9; ABI/ABS)

	Observations	Overall	SCALE	TFP
2005	27,392	20.608	20.195	0.413
2006	23,749	18.133	17.833	0.300
2007	26,085	17.710	17.469	0.241
2008	24,361	16.480	16.240	0.240
2009	24,260	19.740	19.408	0.332
2010	24,259	19.155	18.742	0.414
2011	24,039	15.994	15.680	0.314
2012	24,646	20.728	20.299	0.429
2013	23,637	22.159	21.754	0.405
Average	***24,714***	***19%***	***18.6%***	***0.34%***

Note: TFP measured as residuals of firm gross value added from (industry specific) cost share weighted inputs. Smaller output losses (19%) than the baseline for ABI/ABS (25%).

Robustness and Extensions

- Incorporating labor market distortions
- Alternative calibration values
- Using Solow residuals to measure productivity
- **Dropping imputed default probabilities**
- Using Expected output (instead of actual ex post output)

Dropping imputed default probabilities

- Merging FAME to IDBR results in some non-matched firms (match rate is 70% for ABI/ABS and 54% for IDBR)

- In baseline results we impute missing values in IDBR with a flexible regression based on observables.

- Alternative is to drop all these imputations in Tables A11 (IDBR), A12 (ABI/ABS)

- Slightly larger output losses (e.g. **30.4% vs 27.5%** for IDBR)
  - Similarity because firms with missing PDs tend to be small

Robustness and Extensions

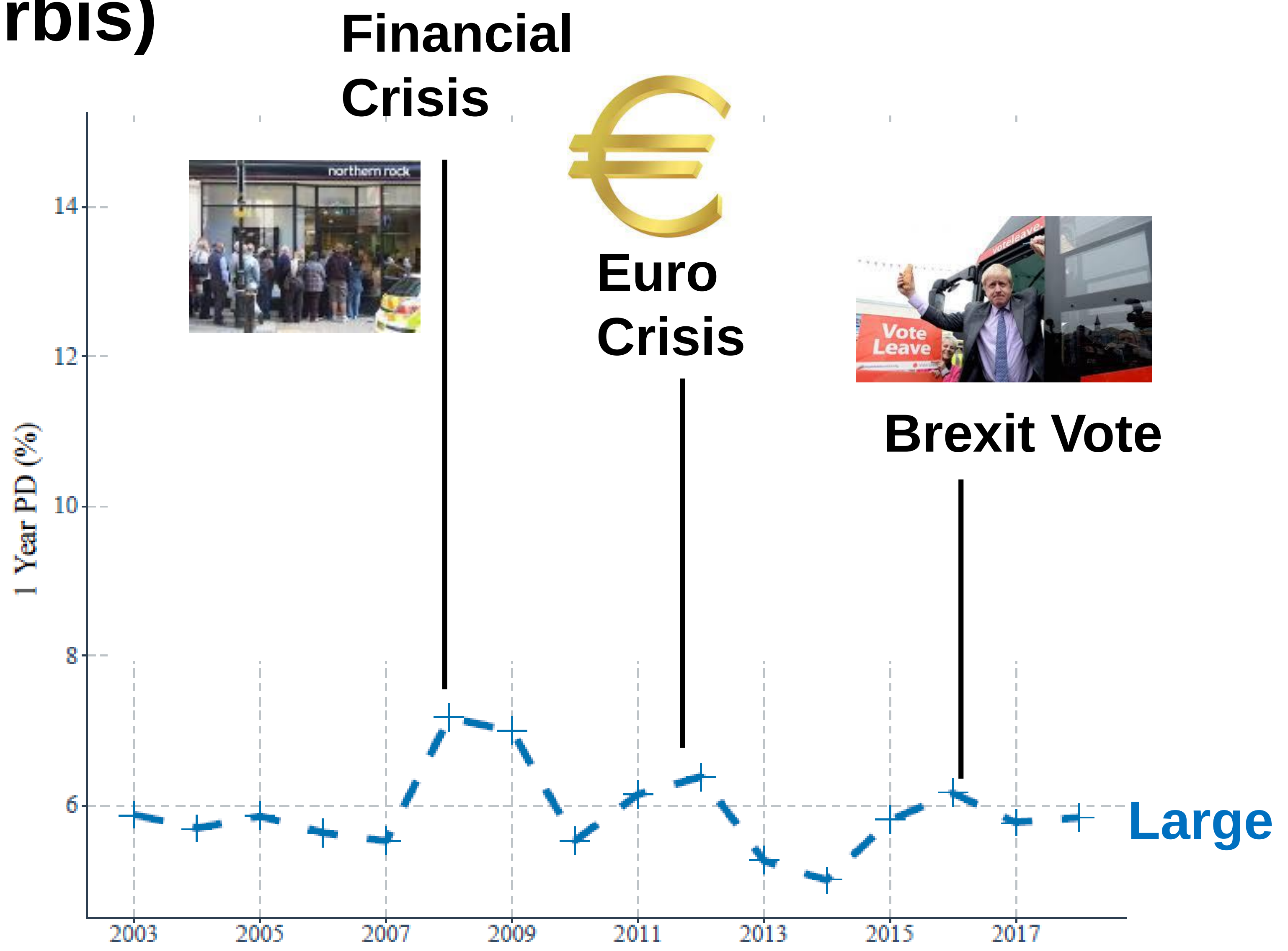
- Incorporating labor market distortions
- Alternative calibration values
- Using Solow residuals to measure productivity
- Dropping imputed default probabilities
- **Using Expected output (instead of actual ex post output)**

Initial Results from New Version

- Include longer time period (**2003-2018)** due to availability of new Historical Orbis database
- Re-run PD models & checking merge into admin data
- For today, focus on analysis using Orbis data only
  - Recover losses using capital information (fixed assets in accounts) rather than labor (from admin data)

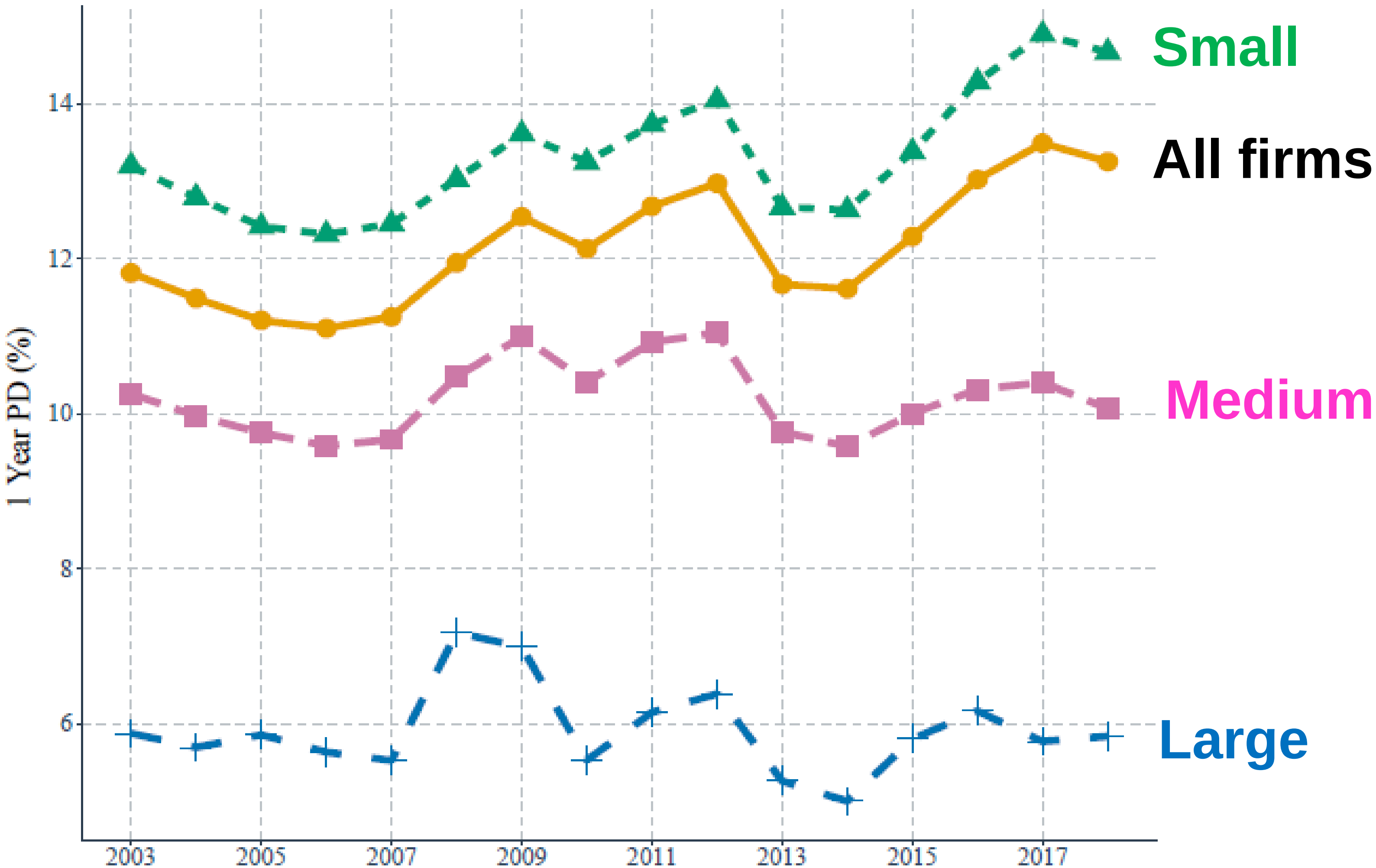
- Overall, broadly similar results
  - Large losses from credit frictions (20%-30%)
  - Much more serious for small firms (and persistent)
  - Credit frictions account for about half of productivity losses during GFC
  - Some new insights (e.g. Brexit)….

Change in mean Default Probabilities (Orbis)



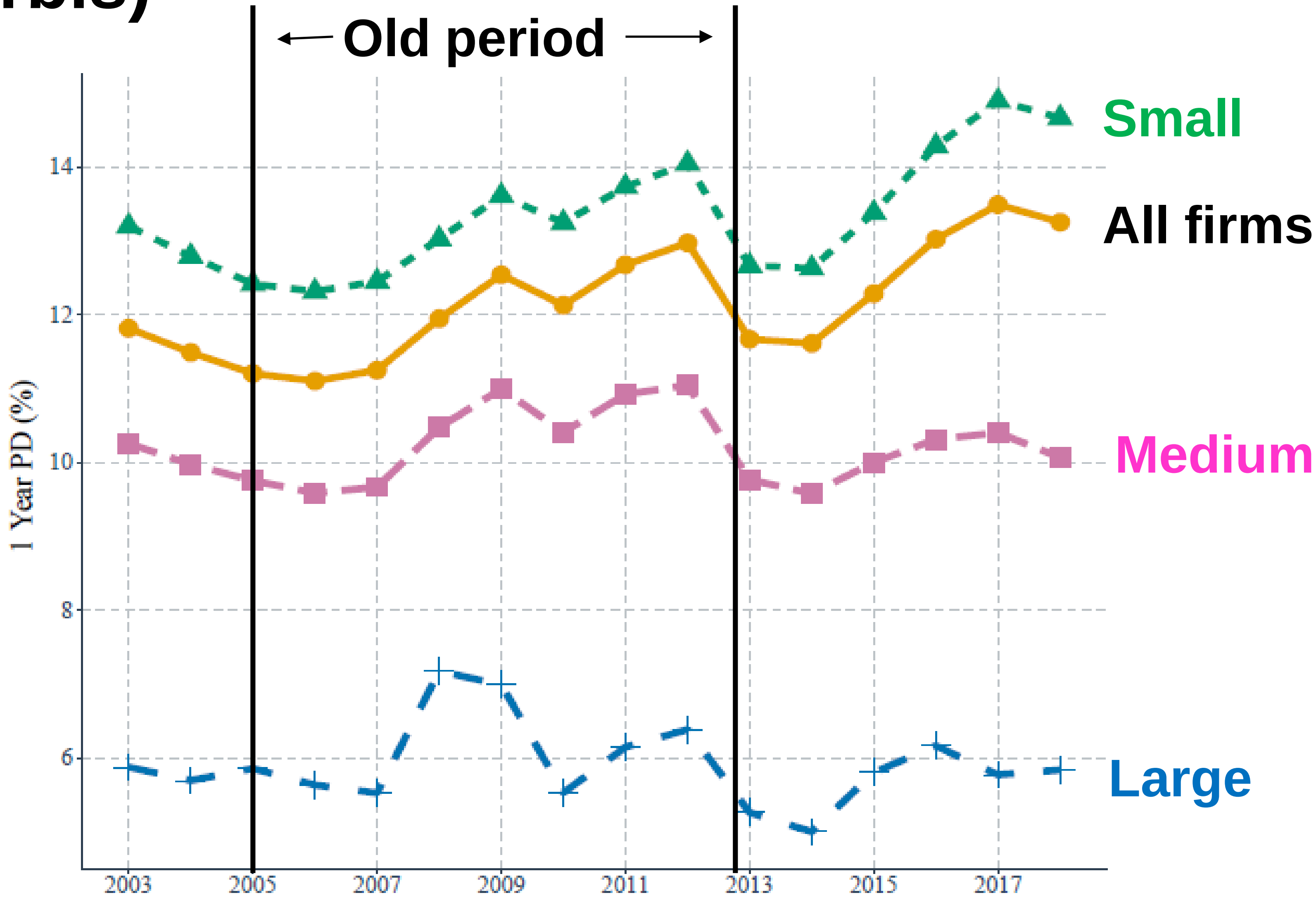
Notes: “Small” firms have under £10,000 in fixed assets; “Medium” are firms with under £20 million in fixed assets and “Large” are firms with over £20 million. Unweighted means.

Change in mean Default Probabilities (Orbis)



Notes: "Small" firms have under £10,000 in fixed assets; Medium are firms with under £20 million in fixed assets and large are firms with over £20 million. Unweighted means.

Change in mean Default Probabilities (Orbis)



Notes: “Small” firms have under £10,000 in fixed assets; Medium are firms with under £20 million in fixed assets and large are firms with over £20 million. Unweighted means.

Conclusions: Summary

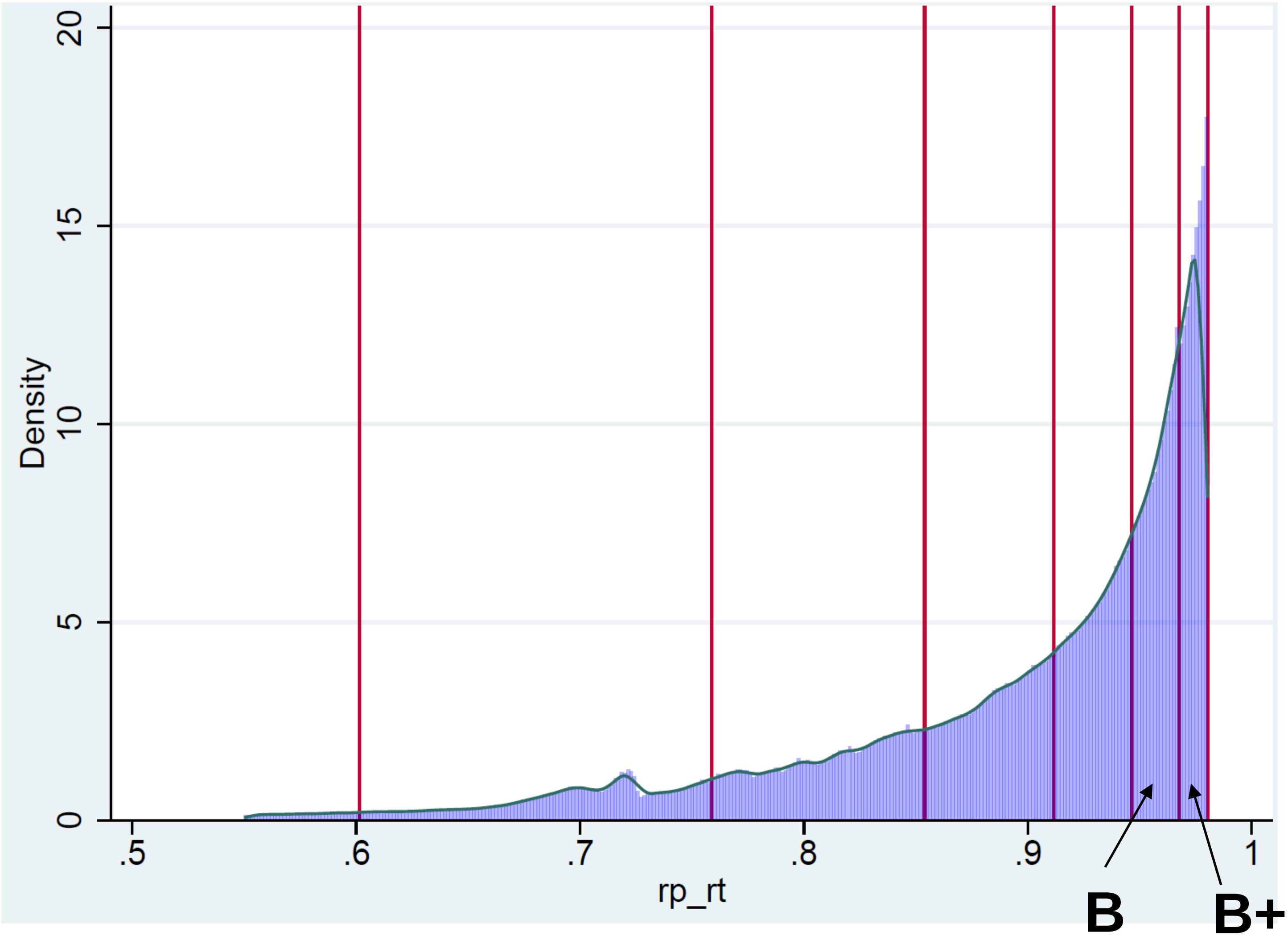
- Develop tractable model with default risk as measure of credit frictions & apply to firm-level default risk & administrative panel data on real side of the economy.

- **Findings**
  - Credit frictions reduced average output by ~28% between 2005-2013
  - Can explain half of productivity loss in Great Recession
  - Losses from credit frictions remain large for SMEs, even long after Great Recession
  - Negative misallocation effects of credit frictions on output much smaller than scale effects (lower aggregate capital)

- **COVID Implications**
  - Important to keep flow of credit during crisis and aftermath, especially for SMEs

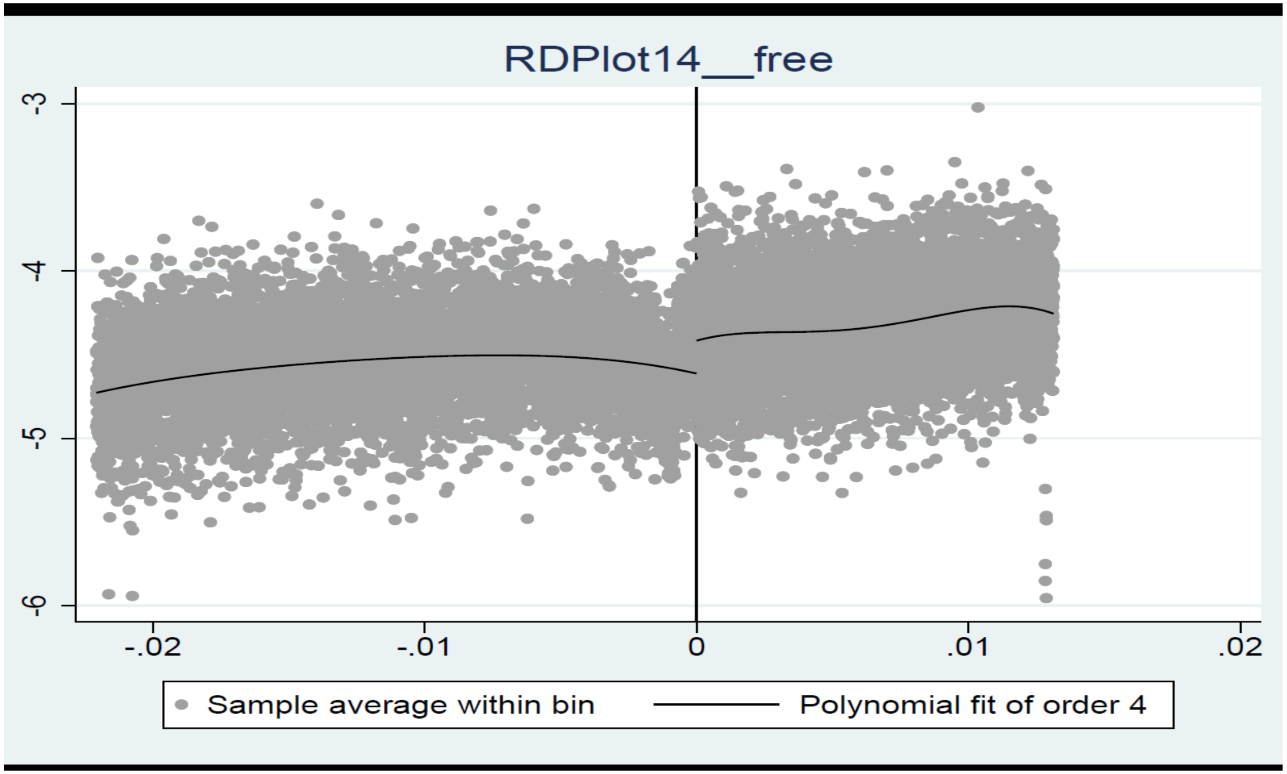
Thanks!

Density is smooth around the cut-offs (raw data on repayment probabilities + kernel fit)



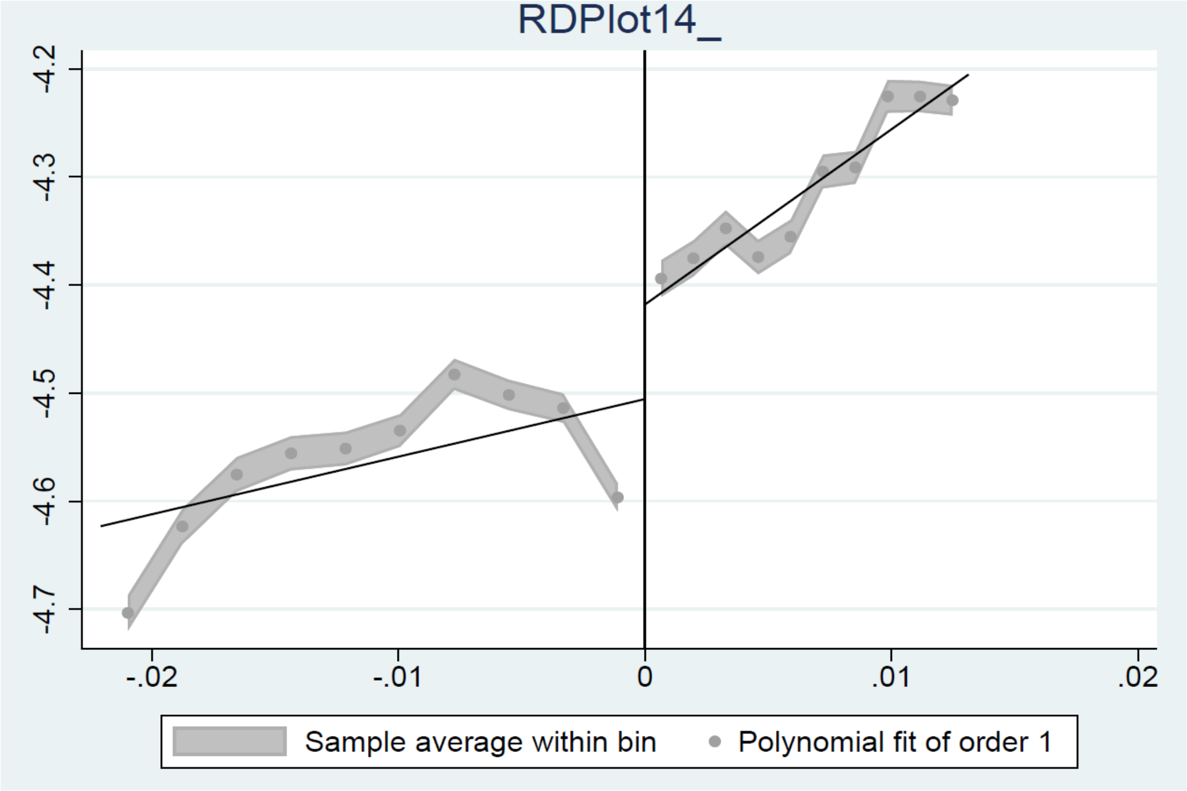
Note: Vertical lines are thresholds between risk bands

Regression Discontinuity for ln(capital) as a function of Credit Score (rating of B+ vs B)



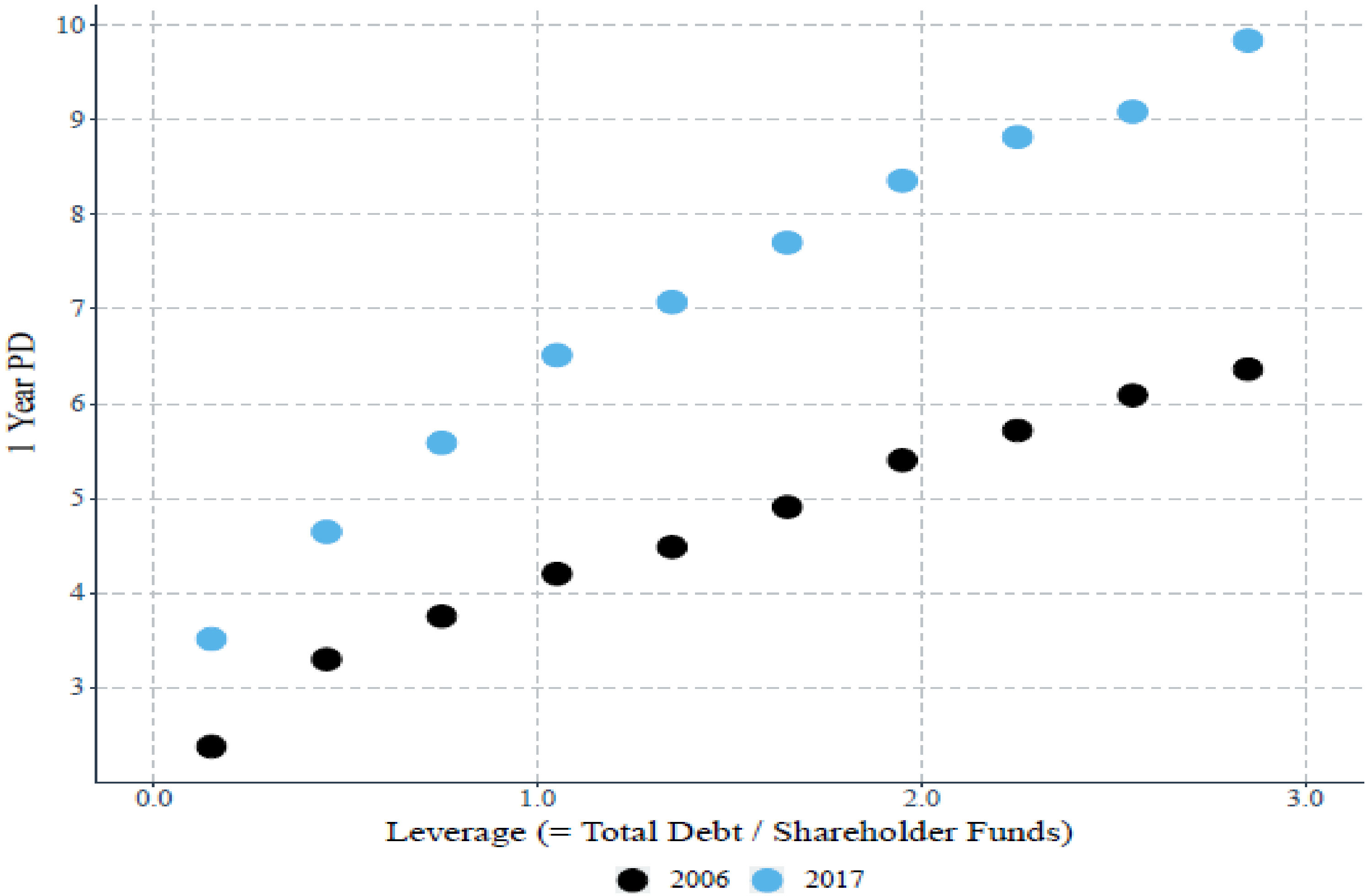
Note: Threshold normalized at zero is at 96.7% chance of repayment. 1.5 million observations pooled 2005-2013 with time dummies. Calonico et al (2014) optimal bandwidth method with 4th order polynomial

Regression Discontinuity for ln(capital) as a function of Credit Score (rating of B+ vs B)



Note: Threshold normalized at zero is at 96.7% chance of repayment. 1.5 million observations pooled 2005-2013. Specification is ln(capital) as a function of threshold, lagged, ln(repayment probability), and time dummies. First order polynomial in running variable (ln(repayment probability)).

Figure 6: Binscatter of 1 Year PD vs Leverage, 2006 vs 2017



Note: Figure shows the relationship between Leverage (defined as the ratio of total debt to shareholder equity) and 1 year probability of default (PD). Results pertain to the 'market sector' industries. See Appendix A for details on sample construction).

Table 9: The effect of credit frictions on aggregate output, weighted by fixed assets

		Overall			Scale		TFP	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	Obs	Θ_t	Output Losses	Growth Contribution	Θ_t^{Scale}	Output Losses	Θ_t^{TFP}	Output Losses
2003	661,726	0.329	0.207	NA	0.364	0.189	0.904	0.019
2004	735,145	0.331	0.207	0.083	0.365	0.188	0.904	0.019
2005	781,400	0.345	0.2	0.909	0.382	0.181	0.904	0.019
2006	829,185	0.379	0.184	1.953	0.413	0.167	0.917	0.016
2007	880,688	0.357	0.194	-1.259	0.393	0.176	0.908	0.018
2008	905,418	0.306	0.219	-3.185	0.341	0.199	0.899	0.02
2009	927,651	0.288	0.229	-1.317	0.324	0.208	0.889	0.022
2010	976,153	0.314	0.215	1.824	0.352	0.194	0.892	0.021
2011	1,047,033	0.289	0.229	-1.701	0.326	0.207	0.888	0.022
2012	1,135,358	0.281	0.233	-0.597	0.319	0.21	0.883	0.023
2013	1,229,250	0.348	0.198	4.423	0.386	0.179	0.9	0.02
2014	1,336,763	0.344	0.2	-0.216	0.383	0.18	0.898	0.02
2015	1,450,954	0.333	0.205	-0.663	0.373	0.184	0.893	0.021
2016	1,548,943	0.228	0.266	-7.917	0.269	0.236	0.847	0.03
2017	1,637,280	0.355	0.195	9.215	0.394	0.175	0.899	0.02
2018	1,709,450	0.333	0.206	-1.33	0.372	0.185	0.895	0.021
Average	1,112,025	0.322	0.212	0.015	0.36	0.191	0.895	0.021

Comparing old (IDBR) vs new (ORBIS)

	Percentage loss of output (Orbis)	Percentage loss of output (IDBR)	Growth contribution (Orbis)	Growth contribution (IDBR)
2003	20.7			
2004	20.7		0.08	
2005	20.0	27.7	0.91	
2006	18.4	26.4	1.95	1.87
2007	19.4	26.0	-1.26	0.51
2008	21.9	25.6	-3.18	0.48
2009	22.9	29.1	-1.32	-4.78
2010	21.5	28.4	1.84	0.97
2011	22.9	28.3	-1.70	0.16
2012	23.3	28.2	-0.60	0.14
2013	19.8	28.2	4.42	0.06
2014	20.0		-0.22	
2015	20.5		-0.66	
2016	26.6		-7.92	
2017	19.5		9.22	
2018	20.6		-1.33	
Average	***21.2***	***27.5***		

-4.5

-4.3

FIGURE A2: Gross Fixed Capital Formation by UK businesses, 2008 Q2=100

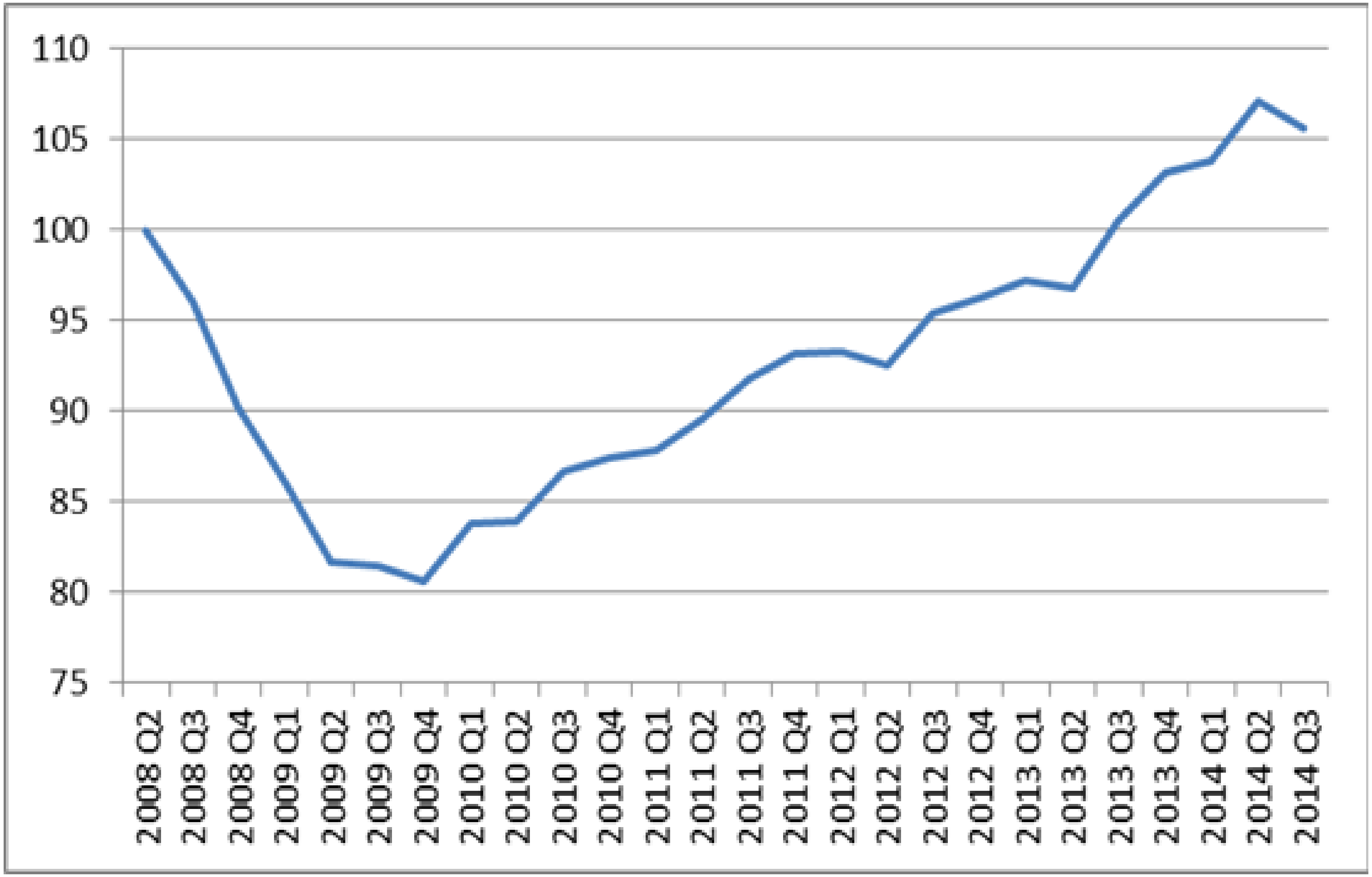
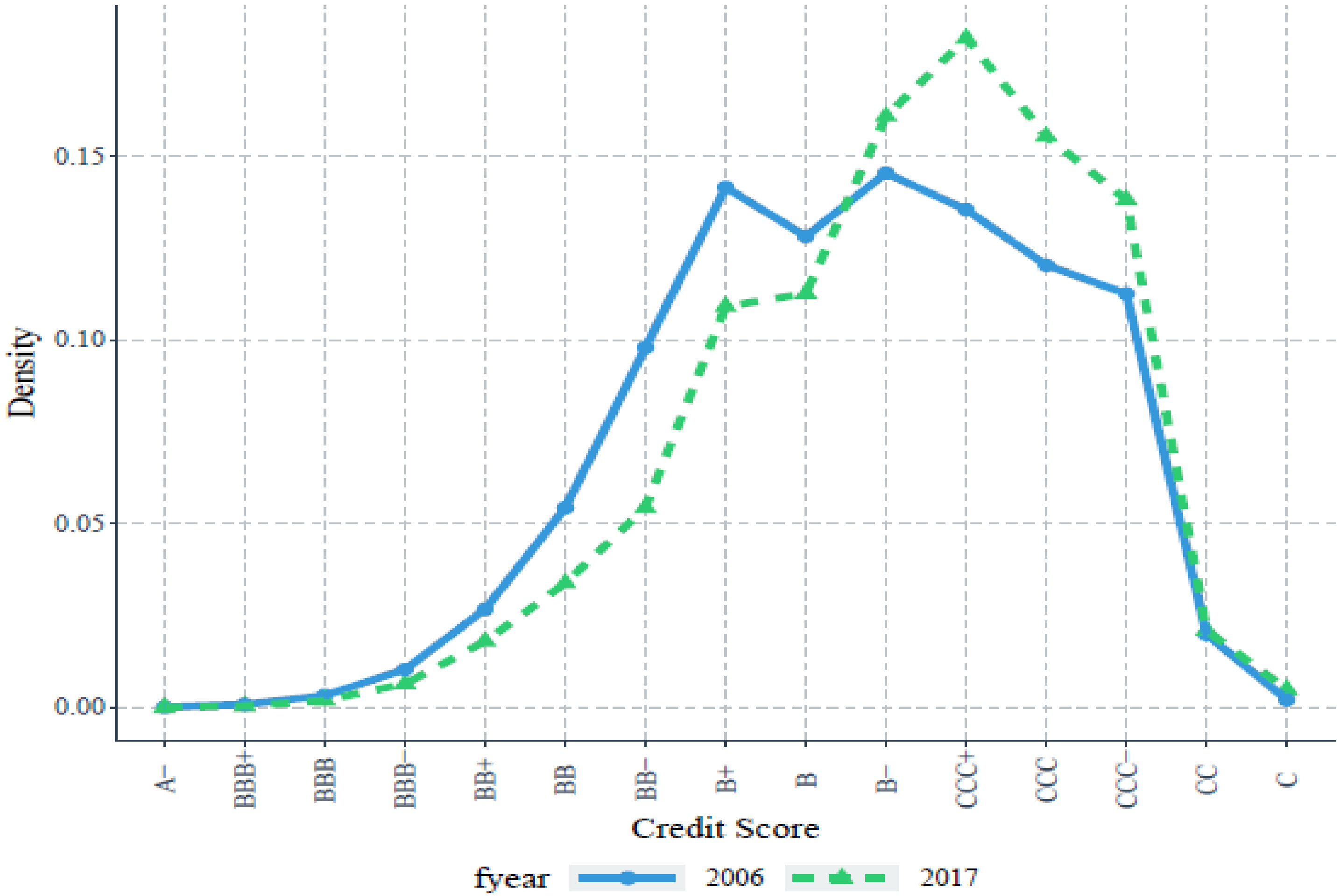
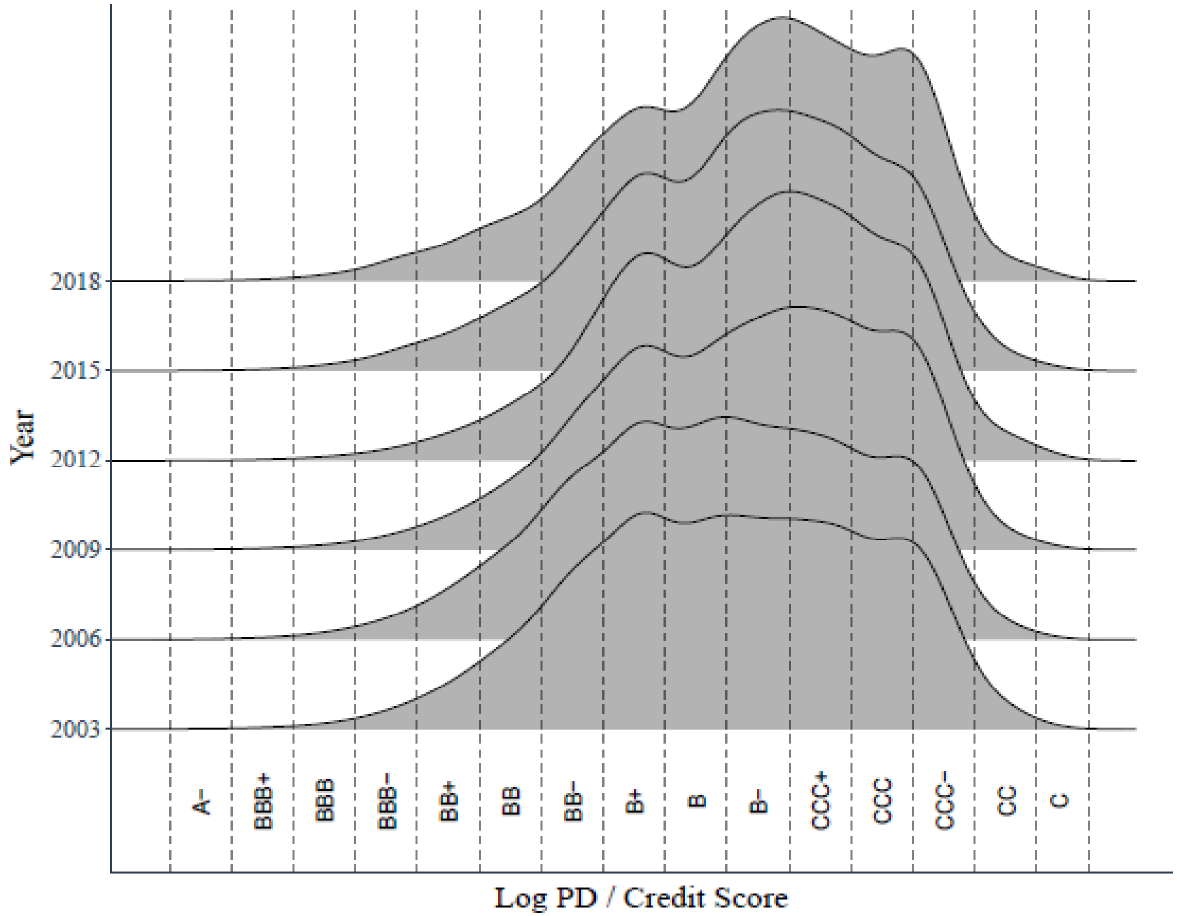


Figure 5: Long Run Change in Distribution of Credit Scores



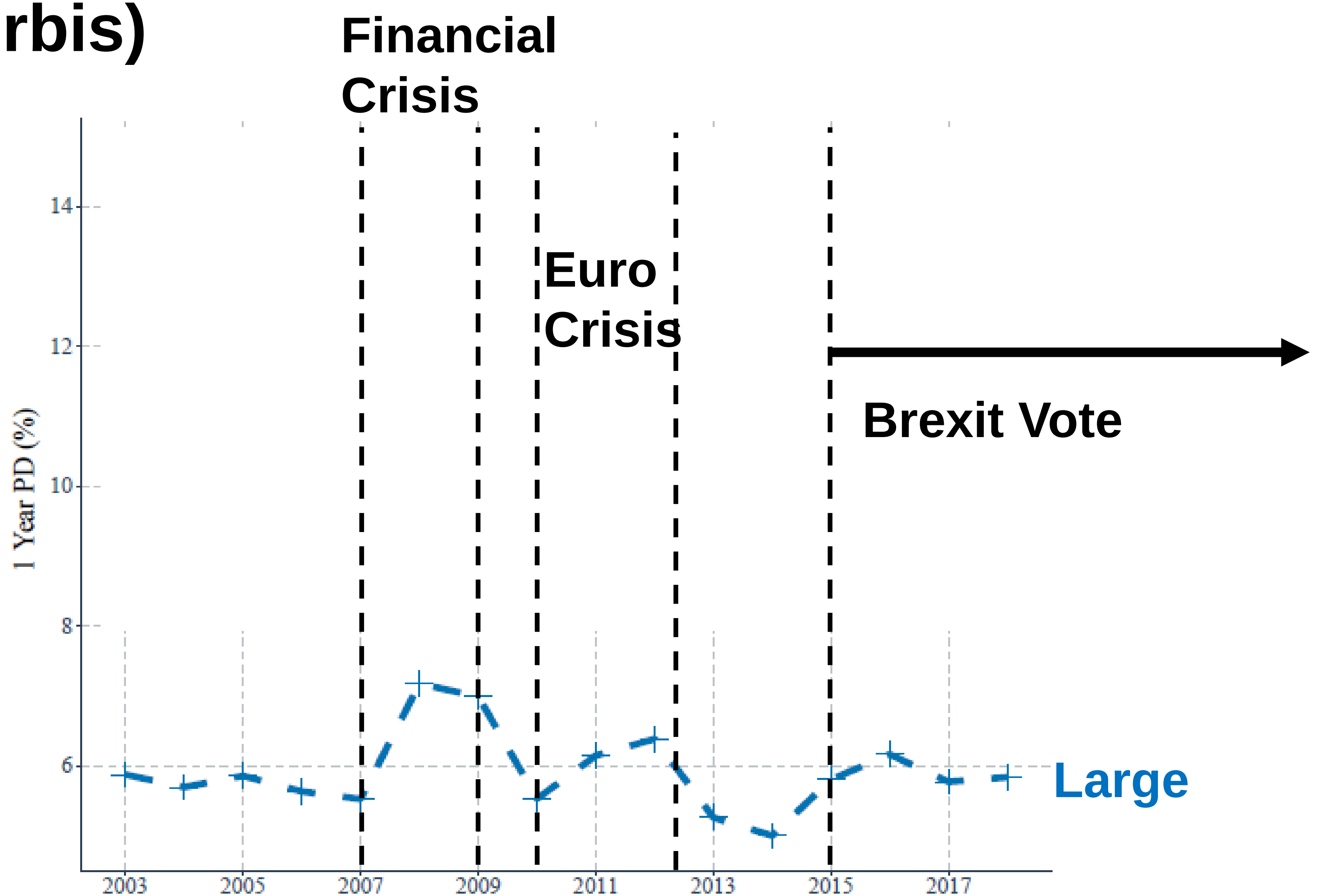
Note: Figure shows the fraction of firms in each of S&P's Credit Score bins. Each of these bins is defined according to the assigned Probability of Default (PD), derived from S&P's CreditAnalytics PD Model. In total, there are 21 Credit Scores, but we omit AAA to A- as these bins contain almost no mass. Results pertain to the 'market sector' industries. See Appendix A for details on sample construction).

Figure 7: Change in Distribution of Log PD / Credit Score



Note: Figure shows the smoothed density plots of the distribution of Log PD over time. The scale of this figure is indicated through dashed lines, which represent the cutoffs that assign Credit Score. The thresholds that assign credit score are almost uniformly spaced in Log PD scale. These thresholds are proprietary information, kindly supplied to us by S&P, thus we do not include the log PD scale values to protect this information. Results pertain to the 'market sector' industries. See Appendix A for details on sample construction).

Change in mean Default Probabilities (Orbis)



Notes: “Small” firms have under £10,000 in fixed assets; “Medium” are firms with under £20 million in fixed assets and “Large” are firms with over £20 million. Unweighted means