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

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Motivation

- Great Recession emphasized link between financial frictions and real economy
- Literature has typically focuses on
  - Large firms for which credit terms publicly visible
  - Impact of misallocation due to distortions
- Pandemic saw large-scale subsidized and targeted 'lending'
- SME credit access is perineal policy objective

Related literature Contributions to literature

This paper

- Develop micro-to-macro model that uses default risk as a sufficient statistic of firm-level credit frictions
- Novel dataset of firm-level default risk matched to universe of administrative firm-level data
- Tractable framework + Novel Data enables us to quantify the aggregate and redistributive role that credit frictions play in the UK before and after GFC
- Covers universe of registered firms (not just large public entities or manufacturing sector)

Related literature

- **Impact of Great Recession via financial frictions:** Chodorow-Reich (2014); Huber (2017); Greenstone et al (2014); Bentolila et al (2015); Schivardi et al (2018); Anderson et al (2019), Lambert & Schindler (2025)
- **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), Faria-e-Castro, Kozlowski, Majerovitz (2025)
- **Misallocation literature:** Restuccia & Rogerson (2008); Hsieh & Klenow (2009, 2014); Bartelsman et al (2013); Asker et al (2014); Hopenhayn (2012, 2014); Baqaee & 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), De Ridder (2024)

Preview of Key Results

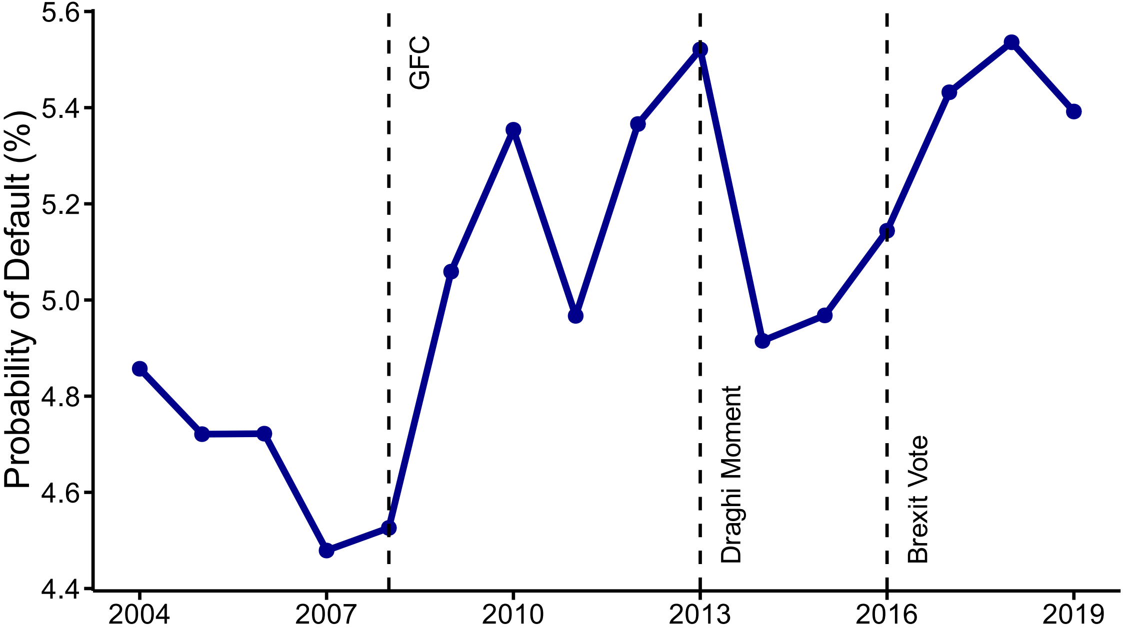
- Credit frictions **reduce aggregate output**
  - Output would grow 15-30% if frictions relaxed
  - Rising frictions drag growth by 0.4pp annually since 2008
- Credit frictions **distort industrial composition**
  - Construction and ICT sectors most constrained
  - Food Services and Professional/Scientific sectors benefit from distortions
- Credit frictions **benefit larger firms** and lower SME output by 55%
- Suppress output **via scale effects** rather than misallocation

Data sources

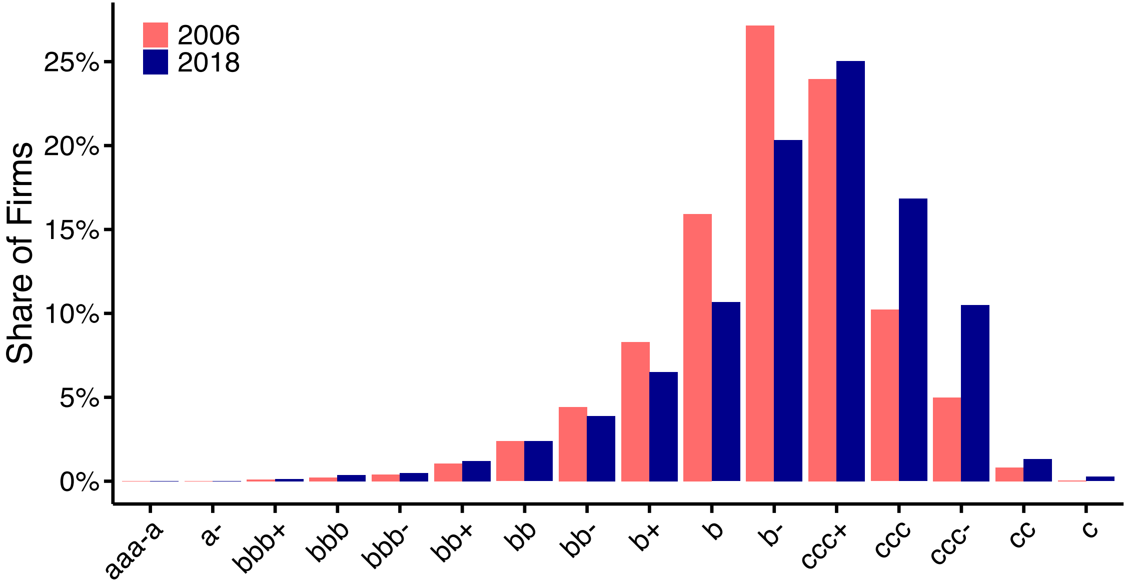
- **Business Structure Database (BSD)**
- **Annual Business Inquiry/Survey (ABI/ABS)**
- **S&P PD Model Algorithm**
  - Forward-looking annual estimate of each firm's **probability of default**.
  - Firm-level financial statements (from BvD ORBIS) combined with proprietary information on industry risk, macroeconomic risk, sovereign risk, and more.
  - Calibrated annually using historical data on actual defaults.

Sample size: 26 million firm-year observations for 2004-2019

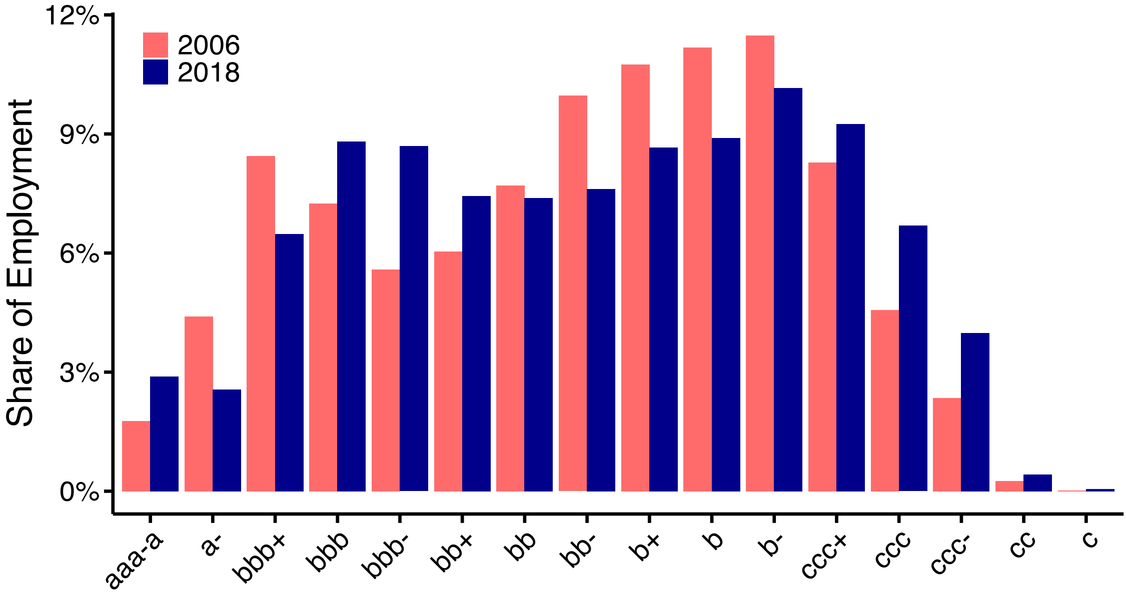
Default Risk rose sharply after 2008 in the UK



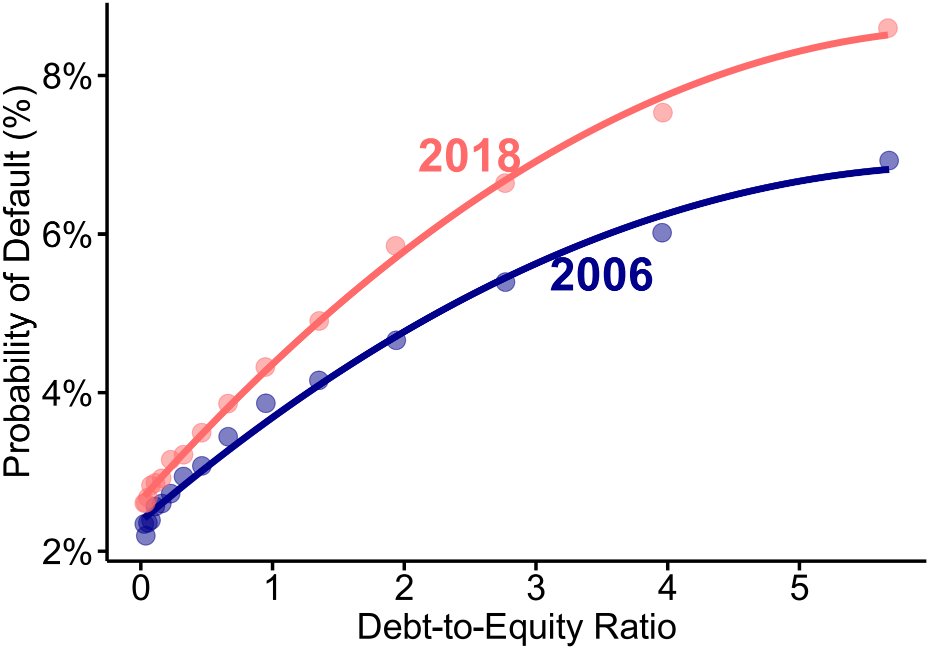
Distribution of Firms by S&P Credit Score



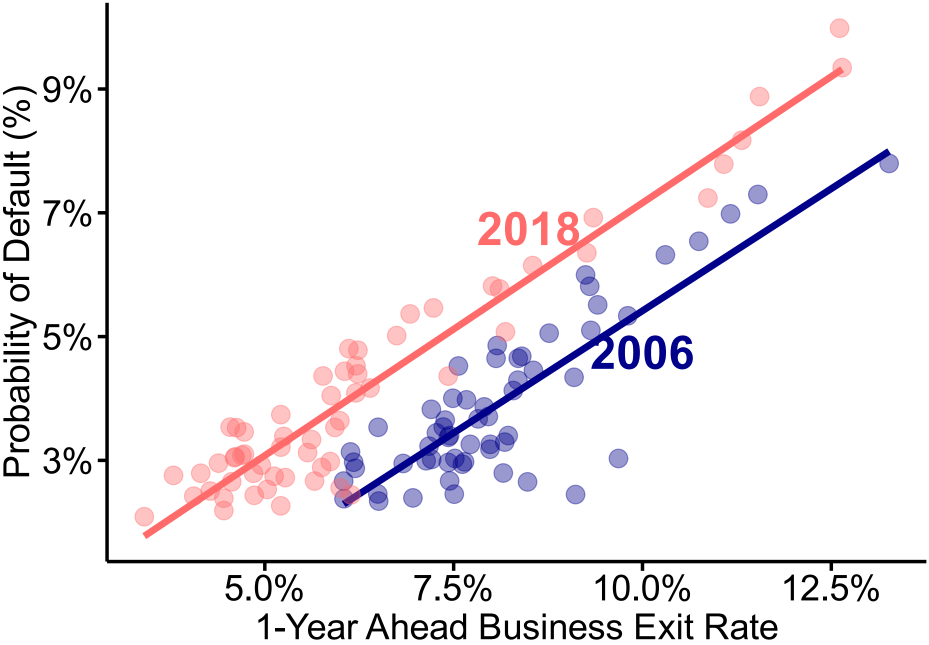
Distribution of Employment by S&P Credit Score



Default risk rise, even relative to D-to-E ratio



Default risk rise, even relative to exit rate



1. Preview of key results
2. Data
3. Theory
4. Key results

Model Blocks

Lending Game:

- Model: Moral hazard pins down idiosyncratic borrowing costs
- Empirics: Default Risk is sufficient statistic for capital distortions

Production:

- Model: Firms optimal factor demands for L & K given factor prices
- Empirics: Quantity of L and price of K recovers TFP and Output

Equilibrium:

- Model: Fixed aggregate L, endogenous wage; perfectly elastic aggregate K
- Empirics: For a given set of distortions, solve for micro-to-macro equilibrium output and distribution of resources

Model Blocks (Gory Details!)

Lending Game & Credit Frictions:

- Banks offer contracts $\{B, R\}$ (borrowing, repayment) with moral hazard. Default occurs with probability ψ_{nst}
- Credit friction wedge: $\tau^K(\psi_{nst}) = \left[1 + \frac{(\Delta+\rho)\psi_{nst}}{(\delta+\rho)(1-\psi_{nst})}\right]^{-1}$ where $(1-\Delta)$ is recovery rate, ρ interest rate
- Firm faces idiosyncratic capital cost: $\dfrac{\rho+\delta}{\tau^K_{nst}}$ with $\tau^K_{nst} \in (0, 1]$, increasing in default risk

Production & Factor Demands:

- Firm production: $Y_{nst} = \theta_{nst}(L_{nt}^{1-\alpha_s} K_{nst}^{\alpha_s})^{\eta_s}$ with TFP θ_{nst}, capital share α_s, returns to scale η_s
- Profit maximization given wage w_t and friction τ^K: $Y_{nst} = a_s \theta_{nst}^{\frac{1}{1-\eta_s}} w_t^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} (\tau^K_{nst})^{\frac{\alpha_s \eta_s}{1-\eta_s}}$
- Sectoral output: $Y_{st} = w_t^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} A_s T_{st}$ where $T_{st} = \sum_n \omega_{nst} (\tau^K_{nst})^{\frac{\alpha_s \eta_s}{1-\eta_s}}$ aggregates firm-level frictions
- Productivity weight (firm's TFP share): $\omega_{nst} = \dfrac{\theta_{nst}^{\frac{1}{1-\eta_s}}}{\sum_m \theta_{mst}^{\frac{1}{1-\eta_s}}}$

Equilibrium & Counterfactuals:

- Labor clearing given fixed supply $\bar{L}_t$: $\bar{L}_t = \sum_s w_t^{-\frac{1-\alpha_s \eta_s}{1-\eta_s}} (1-\alpha_s)\eta_s A_s T_{st}$ determines equilibrium wage w_t
- Sectoral gap (hats denote counterfactual): $\frac{\widehat{Y}_{st}}{Y_{st}} = \frac{\widehat{T}_{st}}{T_{st}} \left(\frac{\widehat{w}_t}{w_t}\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}}$ with direct effect (via T_{st}) and GE effect (via w_t)
- Aggregate gap weighted by shares: $\frac{\widehat{Y}_t}{Y_t} = \sum_s \nu_{st} \left(\frac{\widehat{Y}_{st}}{Y_{st}}\right)$ where $\nu_{st} = \frac{Y_{st}}{\sum Y_{st}}$; Output loss: $\mathcal{G}_t = \frac{\widehat{Y}_t - Y_t}{Y_t}$

Intuition behind GE forces

Output is decreasing in endogenous **Wage** and **Credit Frictions**:

$\uparrow$ **Wage** / $\uparrow$ **Credit Frictions** $\rightarrow$ $\downarrow$ **Output**

But **Wage** falls when **Credit Frictions** grow:

$\uparrow$ **Credit Frictions** $\rightarrow$ $\downarrow$ **Wage** $\rightarrow$ $\uparrow$ **Output**

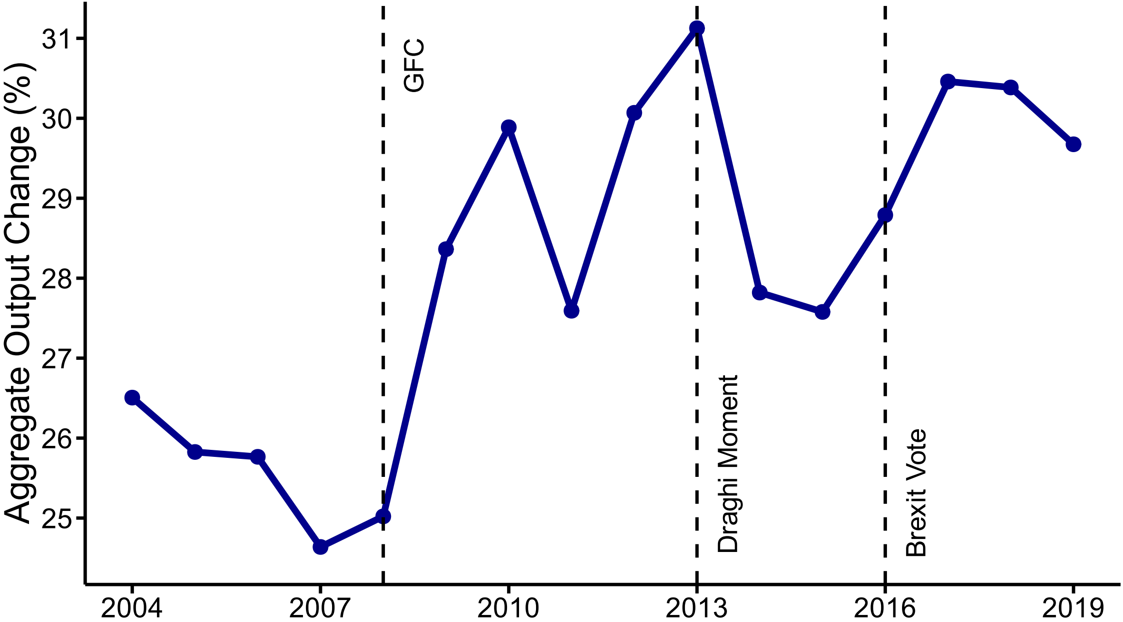
Taking our model to the data

- We use model to compare real economy to counterfactual economy

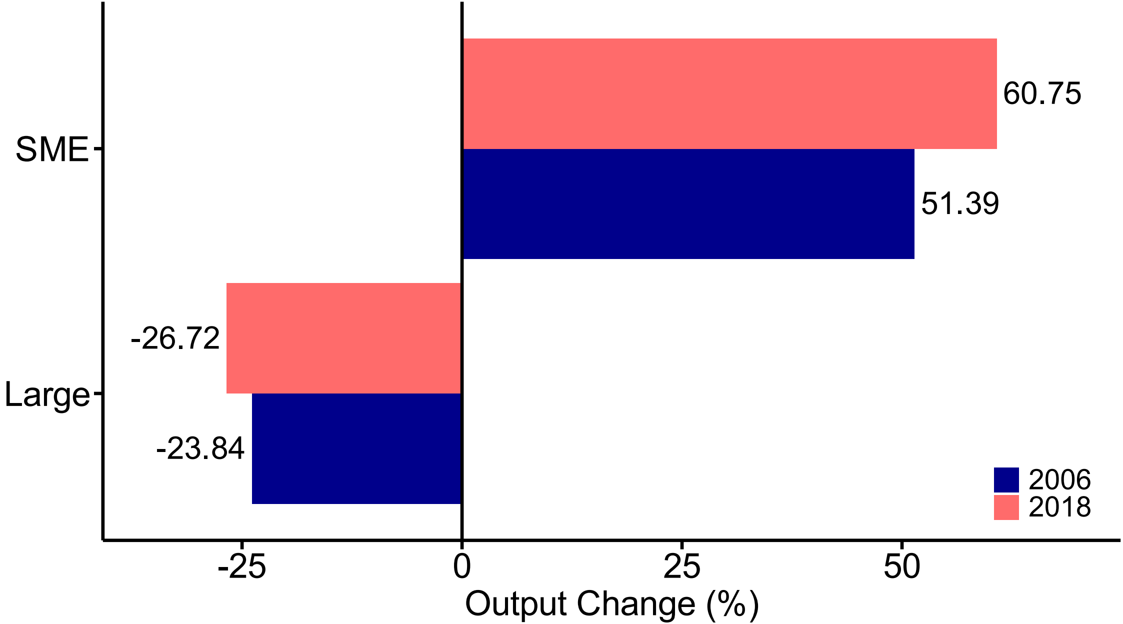
- Use a “low credit-friction” counterfactual.
  - Imposes a price-ceiling on user cost of capital
  - Ceiling set using 5th percentile within each SIC 4-digit industry

- Equivalent to policies which reduced lending frictions

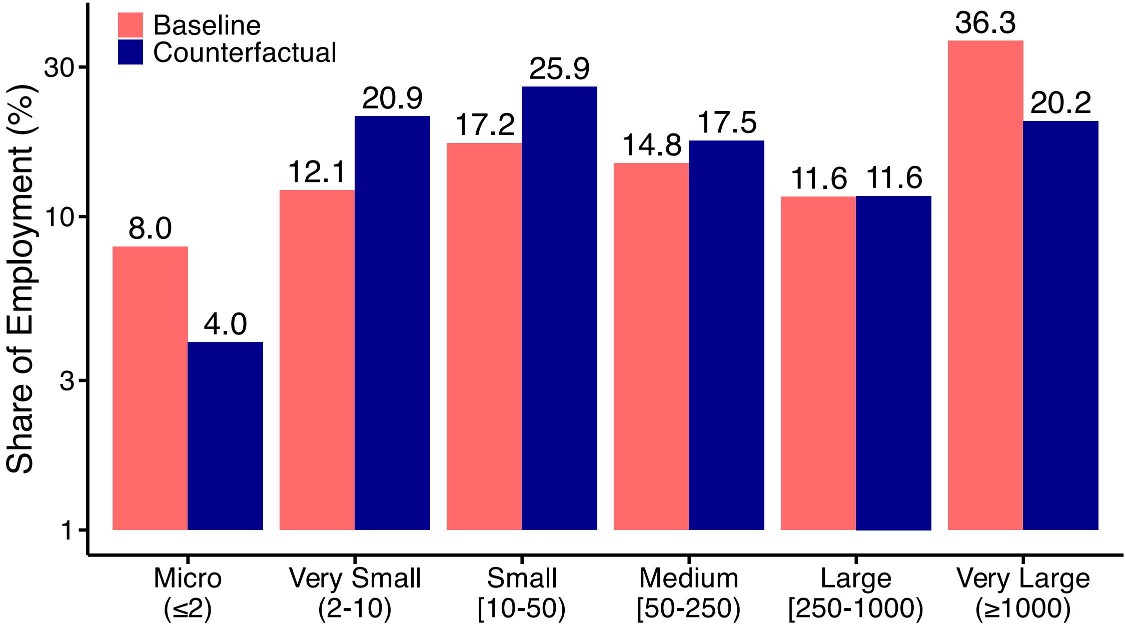
Output gap grows sharply after GFC



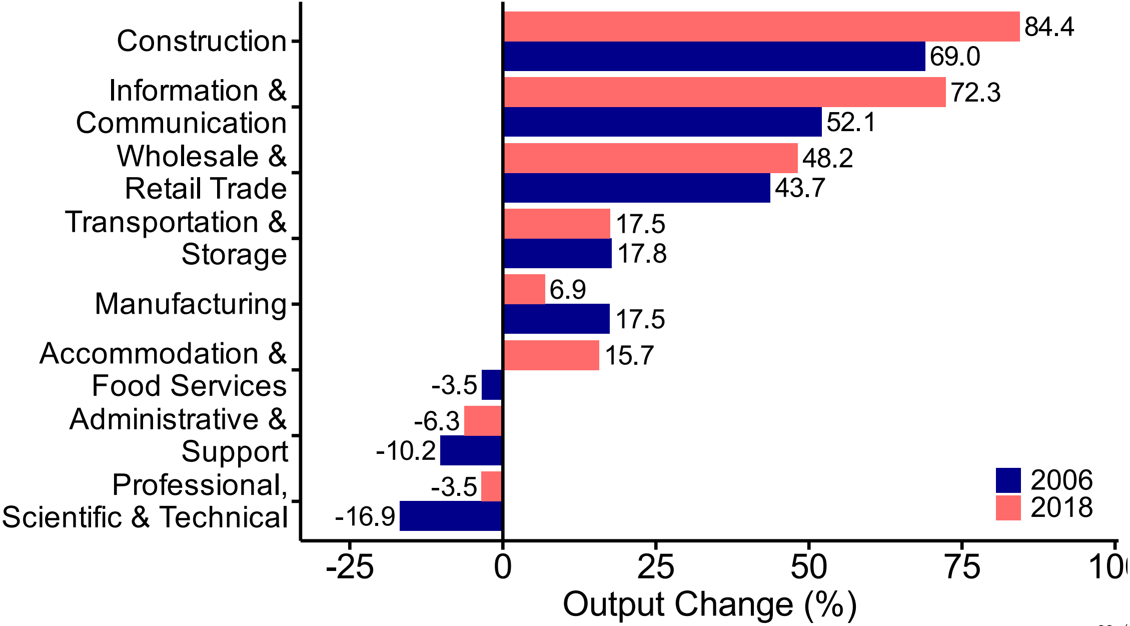
Frictions distort output towards large firms



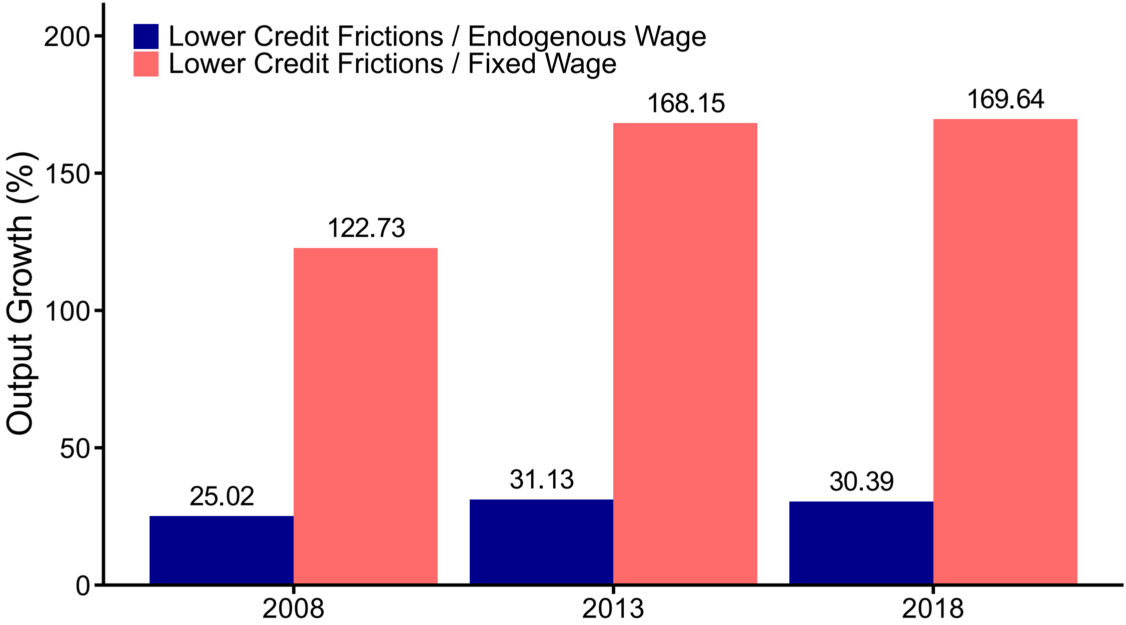
Relaxing frictions compresses firm-size distribution



Relaxing frictions benefits most sectors



GE substantially reduce gains from reducing frictions



Extensions and Robustness

1. Alternative definitions of the **'low friction'** counterfactual
2. Decomposition in the style of **Olley-Pakes** (1998)
3. Allowing for **Labor and Capital** Frictions
4. Fixing Aggregate Capital Stock i.e. canonical **misallocation**
5. Turn off **sectoral heterogeneity**

Conclusions

- Build a **micro-to-macro** model with heterogeneous productivity and capital distortions.
- Leverage **novel micro data** on default risk from S&P algorithm.
- Use model to **quantify impact** of credit market distortions
- The status-quo level of credit market distortions creates **winners and losers**
- Shows importance of **GE and heterogeneity** in policy analysis.

Thank you!

Related literature

- **Impact of GFC on economic activity via financial frictions**
  - Chodorow-Reich (2014); Huber (2018); Greenstone et al (2014); Bentolila et al (2015); Schivardi et al (2018); Anderson et al (2019).
- **Aggregate consequences of firm-level distortions**
  - Midrigan and 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**

Contributions to the literature

- **Tractable framework to document the macroeconomic impact of credit frictions**.
  - Parsimonious data requirements: employment and default risk.
- **Zoom in on credit frictions and measure them directly** - unlike traditional approach based on the marginal product of capital (e.g., Hsieh & Klenow, 2009, Gopinath et al, 2017).
  - Standard approach picks up a wider range of distortions (black box).
  - Standard approach is subject to severe measurement errors in capital and value added.
  - Employment is measured more accurately than capital and value added.
- **Default risk is central to our framework**.

Sector-specific distortions: Comparative statics for α_s and η_s

- Reducing firm-level frictions (increasing τ^K_{nst}) reduces sectoral frictions (increases T_{st}) by more when the sector is more capital intensive (higher α_s).
- Impact of η_s is ambiguous because η_s affects the productivity weights ω_{nst}.
  - ω_{nst} increases in η_s if firm n's productivity (θ_{nst}) is higher than the average productivity of firms in the sector.
  - Conversely, ω_{nst} decreases in η_s if firm n's productivity (θ_{nst}) is lower than the average productivity of firms in the sector.
  - Intuition: A higher η_s (which increases the exponent $\frac{1}{1-\eta_s}$) amplifies existing productivity differences, leading to a greater concentration of output share among more productive firms.

Production function

- This is essentially a Lucas (1978) span of control model where the source of decreasing returns is on the production side and is linked to limits to managerial time.
- Hopenhayn (2014) and Hsieh and Klenow (2009) show that this is equivalent to a model with monopolistic competition where $\eta = 1 - \frac{1}{\epsilon}$ and ϵ is the elasticity of demand.

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Sample size - Universe of registered firms in the market sector

	All		SME			Large		
Year	Employment	Firms	Employment	% of Employment	Firms	Employment	% of Employment	Firms
2003	15,106,365	1,349,696	8,039,457	53.22	1,344,416	7,066,908	46.78	5,280
2004	14,964,551	1,376,901	7,888,049	52.71	1,371,752	7,076,502	47.29	5,149
2005	14,904,267	1,393,810	7,826,383	52.51	1,388,758	7,077,884	47.49	5,052
2006	14,991,964	1,411,649	7,874,549	52.53	1,406,646	7,117,415	47.47	5,003
2007	14,904,124	1,380,881	7,766,348	52.11	1,375,982	7,137,776	47.89	4,899
2008	15,354,987	1,427,139	7,988,488	52.03	1,422,190	7,366,499	47.97	4,949
2009	15,358,240	1,396,289	7,963,124	51.85	1,391,332	7,395,116	48.15	4,957
2010	14,832,258	1,356,886	7,735,769	52.16	1,352,237	7,096,489	47.84	4,649
2011	14,498,250	1,322,655	7,506,644	51.78	1,318,067	6,991,606	48.22	4,588
2012	14,777,566	1,358,590	7,689,252	52.03	1,353,916	7,088,314	47.97	4,674
2013	14,973,057	1,372,654	7,775,166	51.93	1,367,927	7,197,891	48.07	4,727
2014	15,654,351	1,442,619	8,074,369	51.58	1,437,697	7,579,982	48.42	4,922
2015	16,129,897	1,497,406	8,381,398	51.96	1,492,259	7,748,499	48.04	5,147
2016	16,423,182	1,566,935	8,515,479	51.85	1,561,636	7,907,703	48.15	5,299
2017	16,790,430	1,644,546	8,787,745	52.34	1,639,187	8,002,685	47.66	5,359
2018	17,142,192	1,670,645	8,930,932	52.10	1,665,037	8,211,260	47.90	5,608
2019	17,459,691	1,731,074	9,067,709	51.94	1,725,310	8,391,982	48.06	5,764
All	281,851,117	26,488,767	147,031,930	52.17	26,396,892	134,819,187	47.83	91,875

Back

Estimating production parameters (η_s, α_s) with ABI/ABS data

- **Calibrate sector-specific production parameters using two moments from ABI/ABS**:

$$\alpha_s = \frac{\beta_s(1-\chi_s)}{\beta_s + \chi_s}, \quad \eta_s = \frac{\chi_s + \beta_s}{1+\beta_s}$$

- χ_s is the sectoral labour share obtained as:

$$\chi_s = \frac{\sum_{n \in \mathcal{S}} \text{WageBill}_{nst}}{\sum_{n \in \mathcal{S}} ValueAdded_{nst}}$$

- $\beta_s = \frac{\alpha_s \eta_s}{1-\eta_s}$ is estimated from an OLS regression which recovers the elasticity of labour wrt the capital distortion

Estimating production parameters (η_s, α_s)

Table: Microeconometric Estimates of Production Parameters

Industry Section:	(1) Sample Size n	(2) Labor Share χ_s	(3) Regression Coefficient $\widehat{\beta}_s$	(4) Standard Error $SE(\widehat{\beta}_s)$	(5) Implied Parameters α_s	(6) Implied Parameters η_s
C: Manufacturing	118,187	0.48	1.41	0.02	0.39	0.78
F: Construction	55,045	0.47	1.52	0.03	0.41	0.79
G: Wholesale and retail trade	152,499	0.44	1.90	0.03	0.46	0.81
H: Transportation and storage	26,050	0.54	1.94	0.06	0.36	0.84
I: Accommodation and food service	26,937	0.58	1.70	0.06	0.31	0.85
J: Information and communication	35,788	0.46	1.35	0.04	0.40	0.77
M: Professional, scientific and technical	51,936	0.62	1.50	0.04	0.27	0.85
N: Administrative and support service	46,554	0.57	1.47	0.04	0.31	0.83
All Industries:	512,996	0.50	1.62	0.01	0.38	0.81
Standard Calibration values:	-	0.57	1.89	-	0.33	0.85

Measurement: Firm-level distortions τ^K_{nst}

- Theoretical distortion:

$$\tilde{\tau}\left(\psi_{nst}\right) = \frac{1}{1 + \frac{(\Delta+\rho)(1-\psi_{nst})}{(\delta+\rho)\psi_{nst}}} < 1$$

- Empirical equivalent:

$$\tau^K_{nst} = \tilde{\tau}\left(\psi_{nst\,nst}\right) = \frac{1}{1 + \frac{(1+\rho)(1-\psi_{nst\,nst})}{(\delta+\rho)\psi_{nst\,nst}}}$$

  - $(1 - \psi_{nst\,nst})$: Estimated PD from S&P's PD Model.
  - $\rho = \delta = 0.05$ and $\Delta = 1$ (collateral not recoverable).

Back

Measurement of $\frac{T_{st}}{\widehat{T}_{st}}$

- Sectoral credit frictions are:

$$T_{st} = \sum_{n \in \mathcal{S}} \omega_{nst} \tilde{\tau} \left(\psi_{nst\, nst} \right)^{\frac{\alpha_s \eta_s}{1-\eta_s}}$$

- With productivity weight $\omega_{nst} = \frac{\gamma_{nst} T_{st}}{\tilde{\tau}(\psi_{nst\, nst})^{\frac{\alpha_s \eta_s}{1-\eta_s}}}$
  - Where γ_{nst} is the labor share of firm n in sector s.
  - For given γ_{nst}, a relatively more constrained firm must be more productive.
- Since $\sum_{n=1}^{N_{st}} \omega_{nst} = 1$, we have:

$$T_{st} = \left[\sum_{n \in \mathcal{S}} \gamma_{nst} \tilde{\tau} \left(\psi_{nst\, nst} \right)^{-\frac{\alpha_s \eta_s}{1-\eta_s}} \right]^{-1}$$

Measurement of $\frac{\widehat{w_t}}{w_t}$

- Re-write market clearing condition as:

$$1 = \sum_{s=1}^{S} \left\{ \Gamma_{ts} \left(\frac{\widehat{w}_t}{w_t} \right)^{-\frac{1-\alpha_S \eta_S}{1-\eta_S}} \left(\frac{\widehat{T}_{st}}{T_{st}} \right) \right\}$$

- Where $\Gamma_{ts} = \frac{L_{ts}}{L_t}$ is the share of aggregate employment in sector s.
- Solve numerically for $\frac{\widehat{w_t}}{w_t}$ given $\frac{T_{st}}{\widehat{T}_{st}}$ and Γ_{ts}.

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Measurement: Aggregate output losses

- Aggregate output losses can be re-written as a function of observables:

$$\frac{\widehat{Y}_t - Y_t}{\widehat{Y}_t} = 1 - \frac{\sum_{s=1}^{S}\left\{\frac{\Gamma_{ts}}{(1-\alpha_s)\eta_s}\right\}}{\sum_{s=1}^{S}\left\{\frac{\Gamma_{ts}}{(1-\alpha_s)\eta_s}\left(\frac{\widehat{w_t}}{w_t}\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}}\left(\frac{\widehat{T}_{ts}}{T_{ts}}\right)\right\}}$$

- where $\Gamma_{ts} = \frac{L_{ts}}{L_t}$ is the share of aggregate employment in sector s in year t.

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