Cyclical Fluctuations, Financial Shocks, and the Entry of Fast Growing Entrepreneurial Startups.

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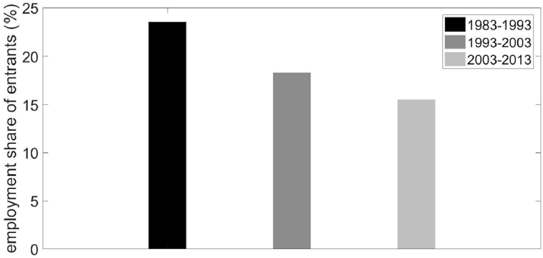
Motivation I

- Entering firms matter for aggregate employment

Figure 5: Employment Share of Entrants



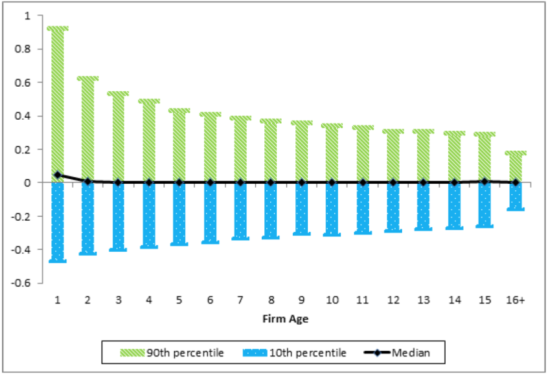
Source: Garcia-Macia, Hsieh and Klenow (2019)

Motivation II

- Employment growth is driven by few young firms that grow very fast

Figure 3

A. Net Employment Growth, 1996-2013, LBD



Source: Haltiwanger et al. (2017)

Motivation III

1. Intrinsic ex-ante characteristics are important for the heterogeneity in growth rates (Pugsley et al. 2018).

   For example:
   - Invent a new restaurant concept with the idea of creating a chain.
   - Open a family restaurant.

2. Individual wealth is important for firm creation (e.g. Holtz-Eakin et al., 1994)

   $\rightarrow$ Financial frictions matter for startup creation.

$\rightarrow$ **Do financial conditions affect the growth potential of new firms through entrepreneurs' decisions?**

This paper

Set-up stylized partial equilibrium model, in which entrepreneurs choose between startups with different growth potential:

- Derive testable predictions on the differential effects of financial frictions.

Use Global Entrepreneurship Monitor (GEM) survey for empirical tests:

- Use survey answers to identify startups with high growth potential.
- Use empirical measures of the cost of external finance that vary over time and across countries.
- Test predictions of the model.
- Quantify employment effects due to *composition of entry* channel.

Preview of findings

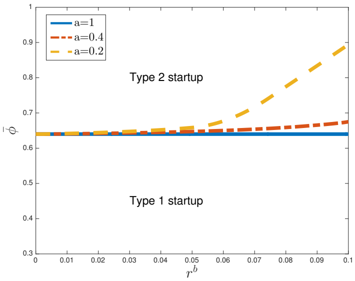
- High-growth startups are more negatively affected by financial shocks than low-growth startups, especially during recessions.
- The composition of entry matters for employment growth:
  - A 1 ppt increase in the cost of finance decreases the share of high-growth startups from 33% to 17% in a recession.
  - This reduces the average employment of new firms by 3.8% after 10 years.

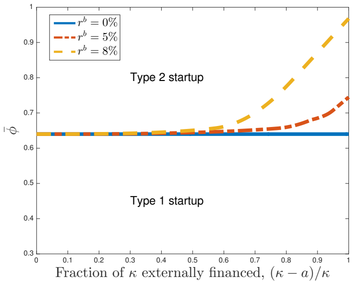
A simple partial equilibrium model

- Many risk neutral entrepreneurs, can create two different types of firms:
  - Type 1: more profitable in short term but low profit growth.
  - Type 2: initially less profitable but higher profit growth later.
- Heterogeneous abilities and costly borrowing to finance initial sunk cost.
- An increase in the lending rate or a higher initial cost increases the cost of finance for Type 2 startups more because it takes longer to repay the debt.

Model - Predictions

- Prediction 1: An increase in the cost of external finance reduces the number of Type 2 relative to that of Type 1 startups.
- Prediction 2: The effects of a higher lending rate and more financing needs reinforce each other.





Global Entrepreneurship Monitor (GEM)

Main dataset: Global Entrepreneurship Monitor (GEM), 21 OECD countries, 2002-2013 period, around 1 million observations.

- Specific questions to identify new entrepreneurs and the kind of startup.
- Representative sample: the firm size distribution obtained from GEM matches well the one obtained from administrative data sources (Poschke, 2018).

Identification of start-ups with high growth potential: entrepreneur expects firm to become large in the next 5 years (relative to average size in the same 2-digit sector).

- Around 35% of all startups are classified as high growth.
- Problem: expectations could be driven by economic prospects.
- Solutions:
  - Add economic expectations as control.
  - Consider predicted financial shocks, orthogonal to news about state of economy.

Do high growth startups have high growth potential?

- SABI dataset (Spain): information on number of employees for all firms started after 2003.
- Each firm is associated with the share of high growth in their 2 digit sector in the year they are born.
- We estimate the effect of these shares on employment growth at different ages.
- Control for sector-year effects and aggregate conditions in the years firms were created.

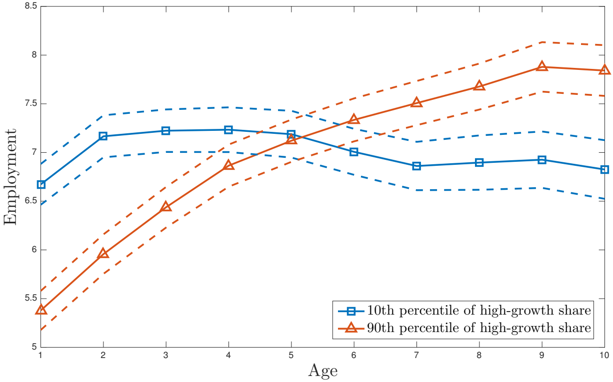
Employment growth

	(1) Empl. growth	(2) Empl. growth	(3) Empl. growth	(4) Employment	(5) Employment	(6) Employment
Age 0 x share				-1.547***	-0.459**	-0.509***
				(0.1380)	(0.1784)	(0.1798)
Age 1 x share	-0.535***	-0.332***	-0.344***	-2.450***	-1.044***	-0.978***
	(0.0435)	(0.0497)	(0.0500)	(0.1438)	(0.1655)	(0.1688)
Age 2 x share	-0.070***	0.073***	0.087***	-2.429***	-0.829***	-0.773***
	(0.0207)	(0.0273)	(0.0277)	(0.1701)	(0.1892)	(0.1887)
Age 3 x share	0.034**	0.077***	0.083***	-1.556***	-0.465**	-0.433**
	(0.0173)	(0.0213)	(0.0216)	(0.1713)	(0.1876)	(0.1933)
Age 4 x share	0.079***	0.020	0.021	-0.585***	-0.285	-0.279
	(0.0160)	(0.0184)	(0.0186)	(0.1836)	(0.2014)	(0.2133)
Age 5 x share	0.056***	0.014	0.022	-0.047	-0.058	-0.097
	(0.0164)	(0.0183)	(0.0186)	(0.1984)	(0.2174)	(0.2337)
Age 6 x share	0.060***	0.047***	0.044**	0.686***	0.222	0.189
	(0.0165)	(0.0179)	(0.0184)	(0.2027)	(0.2220)	(0.2328)
Age 7 x share	0.073***	0.041**	0.041**	1.174***	0.420*	0.442*
	(0.0164)	(0.0180)	(0.0180)	(0.2261)	(0.2487)	(0.2561)
Age 8 x share	0.068***	0.057***	0.056***	1.748***	0.827***	0.802***
	(0.0171)	(0.0188)	(0.0188)	(0.2625)	(0.2935)	(0.2990)
Age 9 x share	0.009	0.078***	0.077***	1.819***	0.943***	0.960***
	(0.0190)	(0.0214)	(0.0214)	(0.2870)	(0.3238)	(0.3219)
Age 10 x share	-0.054**	0.055**	0.058**	1.742***	0.946***	0.841**
	(0.0218)	(0.0250)	(0.0254)	(0.3343)	(0.3667)	(0.3693)
Year FE	Yes	No	No	Yes	No	No
Sector FE	Yes	No	No	Yes	No	No
Year-sector FE	No	Yes	Yes	No	Yes	Yes
Age-growth interactions	No	No	Yes	No	No	Yes
Observations	671652	671652	671652	898797	898797	898797
R-squared	0.112	0.115	0.115	0.149	0.150	0.150

"share" = share of high growth startups in the sector and the year the firm is born

High-growth startup share and ex post firm performance

Figure: Predicted employment by age from SABI



Notes: The 10th percentile is 18%, and the 90th percentile is 66%. The dashed lines show 90% confidence intervals.

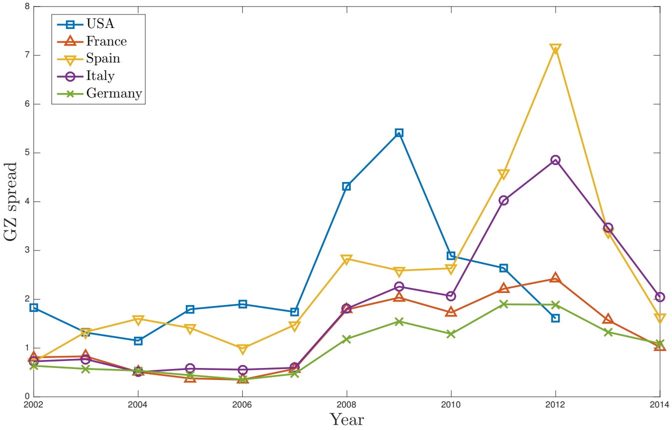
Empirical Strategy

$$Pr(start_{i,j,t} = 1|X_{i,j,t}) = \Phi(\beta_0+\beta_1 Ygr_{j,t}+\beta_2 fin_{j,t}+\beta_3 Ygr_{j,t}\cdot fin_{j,t}+\sum_{k=0}^{N}\gamma_k X^k_{i,j,t}+\varepsilon_{i,j,t}),$$

- $start_{i,j,t} = 1$ is a dummy indicating that individual i in country j in year t is starting a business
- $Ygr_{j,t}$ real GDP growth in country j at time t
- $fin_{i,j,t}$ (benchmark): a financial crisis dummy (from Laeven and Valencia, 2013)
- $fin_{i,j,t}$ (alternative): Credit spreads of financial institutions (Gilchrist and Zakrajsek, 2012)
- $X^k_{i,j,t}$ is a vector of controls including country dummies, gender, age and education.
- **Predictions: β_2 negative, β_3 positive, and both larger for Type 2 startups.**

GZ spread

Figure: GZ spread by country



External financing

Table: Share of external money and GDP growth

	(1) All countries	(2) US and EU4
GDP growth	-0.519***	-1.780***
	(0.1775)	(0.3567)
Year FE	Yes	Yes
Country FE	Yes	Yes
Sector FE	Yes	Yes
Observations	7738	4880
R-squared	0.134	0.148

Notes: The dependent variable is the share of external money needed for a new business calculated from GEM survey answers as one minus the entrepreneur's (expected) own money divided by the required money. We drop observations for which own or required money exceeds one million US$ and for which the own money provided is higher than the required money. EU4 includes France, Germany, Italy and Spain: * p¡0.1, ** p¡0.05, *** p¡0.01.

OLS results

Table: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.663	0.954	-0.012	5.447***	4.418**	6.182***
	(0.7114)	(0.6452)	(0.5684)	(1.9928)	(1.7647)	(1.6892)
Fin. crisis	-0.162***	-0.129***	-0.185***			
	(0.0516)	(0.0412)	(0.0628)			
Fin. crisis x GDP growth	4.679***	3.886***	5.093**			
	(1.7898)	(1.3950)	(2.5150)			
GZ spread				-0.020	-0.013	-0.033*
				(0.0197)	(0.0189)	(0.0173)
GZ spread x GDP growth				2.450	1.532	3.829**
				(1.6126)	(1.3356)	(1.5513)
Observations	894126	894126	894126	370280	370280	370280
R-squared	0.062	0.046	0.077	0.039	0.035	0.039
P-value for $\beta_2^{low} = \beta_2^{high}$		.129			.03	
P-value for $\beta_3^{low} = \beta_3^{high}$		.484			0	

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

IV results

IV strategy:

- Possible endogeneity of GZ spread to other conditions
- Use monthly monetary policy surprise shocks (from Jarocinski and Karadi, 2018) as instruments

IV results

Table: Predicted GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	2.225***	3.025***	-0.550	3.644***	3.081***	3.656***
	(0.7143)	(0.7860)	(1.1896)	(0.3709)	(0.4104)	(0.5919)
GZ spread	-0.037	0.031	-0.197***	0.003	0.025	-0.058*
	(0.0440)	(0.0484)	(0.0731)	(0.0177)	(0.0193)	(0.0301)
GZ spread x GDP growth				1.146***	0.239	2.837***
				(0.3848)	(0.4259)	(0.6255)
Expectations	0.459***	0.417***	0.408***	0.457***	0.417***	0.404***
	(0.0128)	(0.0143)	(0.0200)	(0.0128)	(0.0143)	(0.0200)
Riskless interest rate	0.064***	0.064***	0.043***	0.070***	0.064***	0.058***
	(0.0068)	(0.0075)	(0.0108)	(0.0053)	(0.0058)	(0.0084)
Observations	331184	331184	331184	331184	331184	331184
R-squared	0.067	0.062	0.057	0.067	0.062	0.058
P-value for $\beta_2^{low} = \beta_2^{high}$		.009			.02	
P-value for $\beta_3^{low} = \beta_3^{high}$					.001	

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. The controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p¡0.1, ** p¡0.05, *** p¡0.01.

Additional empirical evidence

Additional evidence: sectors more likely to be financially constrained.

- Startups in "intangibles intensive" sectors (Caggese and Perez, 2018) have higher r^b than in other sectors
- Startups in sectors with more external financial dependence (EFD) need more borrowing b (Rajan and Zingales, 1998)
- Data confirm that startups in intangibles intensive sectors and high-EFD sectors are more sensitive to financial frictions.

The "Composition of entry channel"

- Using the estimates with the predicted spreads and the estimates from SABI, we can calculate the causal effect of financial frictions on future employment growth (abstracting from GE effects) via the "composition of entry" channel.
- During an expansion (GDP growth of 3%)
  - A 1 ppt increase in excess cost of finance reduces the share of high growth startups from 34% to 31%
    $\rightarrow$ Firms born during this period have **0.9% less employment** after 10 years.
- During a recession (GDP growth of -3%)
  - A 1 ppt increase in excess cost of finance reduces the share of high growth startups from 33% to 17%
    $\rightarrow$ Firms born during this period have **3.8% less employment** after 10 years.

Conclusions

1. Firm creation declines when financial frictions are high, even more so during of recession periods.
2. These effects are stronger for startups with high growth potential.
3. Results supports the view that this *Composition of entry* channel is important to explain slow recoveries after financial crises.

Financial crisis data

Table: Countries and financial crisis years

Country	Start year	End year	Obs.
Belgium	2008	2013	28304
Chile	-	-	32911
Croatia	-	-	18972
Denmark	2008	2013	27954
Finland	-	-	21049
France	2008	2013	18687
Germany	2008	2013	60618
Greece	2008	2013	20432
Hungary	2008	2013	21979
Iceland	2008	2013	15547
Ireland	2008	2013	19163
Italy	2008	2013	23210
Japan	-	-	21176
Netherlands	2008	2013	30315
Norway	-	-	18506
Slovenia	2008	2013	27879
Spain	2008	2013	232751
Sweden	2008	2013	39648
Switzerland	2008	2013	18510
United Kingdom	2007	2013	157880
United States	2007	2013	38594

Notes: The periods are systemic banking crises taken from Laeven and Valencia (2013)

Financial dependence data

Table: Sectors and financial dependence

Sector	Name	EFD	Intangible	# start-ups	% high growth
1	Agriculture and hunting	-	low	972	44.3
2	Forestry, logging and related service activities	-	-	79	49.2
5	Fishing	-	-	68	34
14	Other mining and quarrying	-	-	48	50.1
15	Food and Beverages	high	low	441	17.4
17	Textiles	high	high	102	23.9
18	Apparel	-	-	112	60.2
19	Leather	low	low	25	56.5
20	Wood products	high	low	122	41.4
21	Paper products	low	low	12	53.3
22	Printing and publishing	low	high	244	25.9
23	Petroleum and coal	high	low	10	9.3
24	Other chemical products	low	high	85	28.5
25	Rubber and plastic products	high	low	17	32
26	Non-metal products	low	low	67	50.5
27	Iron and steel	high	low	55	30.3
28	Metal products	low	high	87	59.8
29	Machinery	high	high	76	48
30	Office and computing	high	high	16	29.9
31	Electrical machinery	high	high	42	71.4
32	Radio	high	high	16	31.1
33	Professional equipment	high	high	33	30.9
34	Motover vehicles, trailers	low	low	46	11.4
35	Other transport equipment	low	high	22	51.5
36	Furniture	low	high	503	20.7
37	Recycling	-	high	25	13.9
40	Electricity, gas, steam	-	-	167	37.1
41	Collection, purification and distribution of water	-	-	12	44.6
45	Construction	-	high	1774	32.2
50	Sale, maintenance, repair of motor vehicles	-	low	769	37.1
51	Wholesale and commission trade	-	high	1280	26
52	Retail trade	-	low	4297	33.2
55	Hotels and restaurants	-	low	2156	35.5
60	Land transport; transport via pipelines	-	-	523	29.6
61	Water transport	-	-	15	23.1
63	Supporting and auxiliary transport activities	-	-	381	40.9
64	Post and telecommunications	-	-	178	39
71	Renting of machinery and equipment	-	high	85	30
72	Computer and related activities	-	high	1066	29
73	Research and development	-	high	87	55
85	Health and social work	-	low	1839	31.1
90	Sewage and refuse disposal, sanitation	-	-	125	47.8
91	Activities of membership organizations n.e.c.	-	-	60	25
92	Recreational, cultural and sporting activities	-	low	1454	35.9
93	Other service activities	-	-	1169	41
95	Activities of private households as employers of domestic staff	-	-	31	43.5
Total				20793	33.9

Notes: External dependence based on Kroszner et al. (2007) and intangible share based on Caggese and Perez (2018).