

"Heterogeneous Innovation over the Business Cycle"

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Research question

- Innovation should be countercyclical (Cooper and Haltingwanger, 1993; Caballero and Hammour, 1994; Aghion and Saint-Paul, 1998; Canton and Uhlig, 1999).
- Evidence goes in the opposite direction:



 Credit constraints (Aghion et al 2007); risk aversion (Rampini 2004); externalities in R&D (Barlevy 2007);



This Paper

- Different types of innovation (exploration versus exploitation)
- Theoretical model exploration and exploitation over the business cycle –Exploration is countercyclical, exploitation is procyclical
- Develop clear metrics of firm level exploration/exploitation
 - Principal component anlysis (PCA) of readily available patent portfolio measures
- Validate these measures against some outcomes
- Study exploration and exploitation over the business cycle



The Model Without Macro Shocks

- Agents live two periods and are risk neutral with zero discounting
- Representative firm chooses between a well-known or a novel action
- Well-known action has a known probability p of success. Novel action has an unknown probability q of success.
- The novel action is of exploratory nature:

E[q]



Action Plans

• Only two action plans need to be considered

-Exploitation: take the well known action in both periods

-Exploration: take the novel action in the first period and stick to it only if success is obtained.



Action Plans







Optimal Choice •Exploration is better than exploitation iff

$$E[q] \ge \frac{1}{(1 + (E[q|S] - p))} p$$

•More periods? Teams?



Adding Macro Shocks to the Model

• Macroeconomic state *m* can be either high (H) or low (L)

• If the macroeconomic state is *m* it remains in the same state next period with probability ρ_m . Alternatively it transitions into the other state *n* next period.

• Output in each period is given by *m*S in case of success and *mF* in case of failure.



Action Plans





Payoffs

• Exploitation:

 $pmS + (1-p)mF + \rho_m (pmS + (1-p)mF) + (1-\rho_m)(pnS + (1-p)nF)$

• Exploration:

$$\begin{split} E[q]mS + (1 - E[q])mF + \rho_m \left(E[q](E[q|S]mS + (1 - E[q|S]))mF \right) + (1 - E[q])(E[q|F]mS + (1 - E[q|F])mF) \right) + (1 - \rho_m)(E[q](E[q|S]nS + (1 - E[q|S])nF) + (1 - E[q])(pnS + (1 - p)nF)) \end{split}$$



Optimal Choice

• Exploration is better than exploitation iff:

$$E[q] \ge \frac{m}{n(E[q|S] - p)(1 - \rho_m) + m(1 + (E[q|S] - p)\rho_m))} p$$

• The threshold is increasing in m and decreasing in n.

-Exploration more common in recessions

-Exploitation more common in booms



Optimal Choice

• Exploration is better than exploitation iff:

$$E[q] \ge \frac{m}{n(E[q|S] - p)(1 - \rho_m) + m(1 + (E[q|S] - p)\rho_m))} p$$

• The threshold is increasing in ρ_L and decreasing in ρ_H .

-Exploration less common if recessions are long-lasting

-Exploration more common if booms are long-lasting



For now just 1977-2001

Table 1 – Frequency count of firm-year patent portfolio observations.

24,163

Total:

Frequency	Percent	Cum.	Table 2 – Summary st	tatistics					
718	2.97	2.97	v						
718	2.97	5.94	Variable	Ν	mean	Median	sd	min	max
747	3.09	9.03	Patents	24163	34.26	4	137.2	1	4054
756	3.13	12.16	Top 1%	24163	0.484	0	1.795	0	41
765	3.17	15.33	Top 5-2%	24163	1.601	0	5.813	0	164
770	3.19	18.52	Top 10-6%	24163	2.457	0	8.665	0	258
763	3.16	21.67	Top 25-11%	24163	7.381	1	27.35	0	845
783	3 24	24.91	Top 50-26%	24163	11.70	2	45.38	0	1365
831	3.44	28.35	No cite	24163	1.693	0	8.834	0	278
031	2.44	20.55	All future cites	24163	669.1	77	2882	0	120444
852	5.44 2.54	31.8	New tech classes entered	24163	2.539	1	4.559	0	89
855	3.54	35.34	Patents in new classes	24163	3.016	1	6.183	0	185
873	3.61	38.95	Patents in known classes	24163	31.25	3	134.4	0	4051
844	3.49	42.44	Technological proximity	24163	0.541	0.581	0.328	0	1
877	3.63	46.07	Av. age of inventors	24163	3.633	3.063	3.131	0	26
937	3.88	49.95	Backward citations	24163	331.0	41	1387	0	48540
1.024	4.24	54.19	Self-citations	24163	42.55	1	280.6	0	11413
1 106	4 58	58 76	Claims	24163	528.5	66	2357	1	85704
1,100	1.00	63.60	Patent stock	24163	312.7	23	1279	0	34942
1,191	+.95 5 50	(0.07	<i>Notes:</i> This table reports summ	nary statistics of	f variables used	d in the study. Pa	tents is the total	number of eve	entually granted
1,348	5.58	69.27	3-digit technology class and ar	year. Top 1% a polication year.	Top 5% to 2%	are the number of	f natents that fal	1 into the 5% to	2% most cited
1,315	5.44	74.71	patents within a given 3-digit	technology clas	s and application	on year. Top 10%	to 6% are the r	number of pate	nts that fall into
1,347	5.57	80.29	the 10% to 6% most cited particular	tents within a g	given 3-digit te	chnology class a	nd application y	vear. Top 25%	to 11% are the
1,323	5.48	85.76	number of patents that fall int	o the 25% to 1	1% most cited	patents within a	given 3-digit teo	chnology class	and application
1,232	5.1	90.86	technology class and application	e number of pa on year 'No ci	tents that fall iter the num	into the 50% to 2 ber of patents the	26% most cited at are not cited l	patents within by any other particular	a given 3-digit
1,141	4.72	95.58	cites is the total number of fu	ture citations. I	New classes ent	tered is the numb	er of technolog	y classes where	e a firm filed at
1,067	4.42	100	least one patent but no other pa	atent beforehand	l. Patents in nev	w/known classes i	s the number of	patents that are	e filed in classes

technology class and application year. 'No cite' are the number of patents that are not cited by any other patent. All future cites is the total number of future citations. New classes entered is the number of technology classes where a firm filed at least one patent but no other patent beforehand. Patents in new/known classes is the number of patents that are filed in classes where the given firm has filed no/at least one other patent beforehand. Technological proximity is the technological proximity between the patents filed in year t to the existing patent portfolio held by the same firm up to year *t*-1, calculated according to Jaffe (1989). Av. Age of inventors the average time difference between the first time an inventor occurs in the Fung Institute's patent database and the application year of a given patent. Backward citations is the total number of citations made to other patent. Self-citations is the total number of cites to patents held by the same firm. Claims is the total number of claims on each patent. Patent stock is the sum of all patents held by a given firm up to the year *t*-1.



Table 3 - Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	Patents	1.00															
(2)	Top 1%	0.66	1.00														
(3)	Top 5-2%	0.80	0.73	1.00													
(4)	Top 10-6%	0.84	0.80	0.82	1.00												
(5)	Top 25-11%	0.92	0.68	0.87	0.83	1.00											
(6)	Top 50-26%	0.95	0.69	0.78	0.88	0.86	1.00										
(7)	No cite	0.76	0.55	0.65	0.67	0.70	0.73	1.00									
(8)	All future cites	0.87	0.65	0.77	0.81	0.87	0.85	0.55	1.00								
(9)	New tech classes entered	0.71	0.45	0.55	0.58	0.64	0.67	0.52	0.61	1.00							
(10)	Patents in new classes	0.71	0.45	0.55	0.59	0.64	0.67	0.52	0.62	0.99	1.00						
(11)	Patents in known classes	0.97	0.64	0.78	0.82	0.90	0.93	0.75	0.84	0.56	0.56	1.00					
(12)	Technological proximity	0.32	0.17	0.23	0.25	0.29	0.30	0.19	0.32	-0.03	-0.03	0.42	1.00				
(13)	Av. age of inventors	0.15	0.07	0.11	0.12	0.14	0.14	0.12	0.15	-0.07	-0.06	0.21	0.17	1.00			
(14)	Backward citations	0.91	0.59	0.73	0.77	0.85	0.87	0.64	0.85	0.62	0.63	0.89	0.33	0.22	1.00		
(15)	Self-citations	0.87	0.63	0.75	0.78	0.84	0.85	0.68	0.77	0.47	0.47	0.89	0.35	0.27	0.85	1.00	
(16)	Claims	0.94	0.61	0.75	0.79	0.87	0.89	0.68	0.86	0.65	0.65	0.91	0.33	0.20	0.91	0.84	1.00
(17)	Patent stock	0.83	0.53	0.65	0.69	0.76	0.79	0.66	0.68	0.46	0.45	0.87	0.19	0.27	0.77	0.82	0.78

Notes: This table reports pairwise correlations of the log-transformed variables used in the study. Patents is the total number of eventually granted patents applied for in a given year. Top 1% are the number of patents that fall into the 1% most cited patents within a given 3-digit technology class and application year. Top 5% to 2% are the number of patents that fall into the 5% to 2% most cited patents within a given 3-digit technology class and application year. Top 10% to 6% are the number of patents that fall into the 10% to 6% most cited patents within a given 3-digit technology class and application year. Top 25% to 11% are the number of patents that fall into the 25% to 11% most cited patents within a given 3-digit technology class and application year. Top 50% to 26% are the number of patents that fall into the 50% to 26% most cited patents within a given 3-digit technology class and application year. 'No cite' are the number of patents that are not cited by any other patent. All future cites is the total number of future citations. New classes entered is the number of technology classes where a firm filed at least one patent but no other patent beforehand. Patents in new/known classes is the number of patents that are filed in classes where the given firm has filed no/at least one other patent beforehand. Technological proximity is the technological proximity between the patents filed in year t to the existing patent portfolio held by the same firm up to year t-1, calculated according to Jaffe (1989). Av. Age of inventors the average time difference between the first time an inventor occurs in the Fung Institute's patent database and the application year of a given patent. Backward citations is the total number of citations made to other patents. Self-citations is the total number of cites to patents held by the same firm. Claims is the total number of claims on each patent. Patent stock is the sum of all patents held by a given firm up to the year t-1.



Tables 4 and 5 – Principal Component Analysis

Component	Variance	Difference	Proportion	Cumulat	ive
Comp1	4.02	1.72	0.50	0.50	\mathcal{T}
Comp2	2.30		0.29	0.79	

Notes: This table reports the results of a Principal Component Analysis after Varimax Rotation. Only components with Eigenvalues above one are extracted. The 8 variables that entered the PCA are: new classes entered, patents in new/known classes, technological proximity, av. age of inventors, backward citations, self-citations, and claims; all variables log-transformed.

Variable	Comp1	Comp2	Unexplained
New tech classes entered		0.58	0.08
Patents in new classes		0.58	0.08
Patents in known classes	0.45		0.09
Technological proximity	0.39	-0.38	0.47
Backward citations	0.41		0.10
Self-citations	0.45		0.16
Claims	0.41		0.09
Av. age of inventors	0.31	-0.37	0.60

Notes: This table reports the results of a Principal Component Analysis after Varimax Rotation. Only components with Eigenvalues above one are extracted. All variables log-transformed. Variable definitions provided above.



Figure 1 – Scatter Plot of PCA scores



Notes: This graph plots the component scores of 'Exploration' and 'Exploitation' extracted from the Principal Component Analysis shown above. Red lines mark the median values of each factor. 19% of the observations are each in the upper left and lower right quadrants, 31% in each of the other quadrants.

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An inexorable exploitation path dependence (except of course for Intel)?





	a	b	с	d	e	f	g
Dependent variable	Тор 1%	Top 5-2%	Top 10- 6%	Top 25- 11%	Top 50- 26%	Not cited	All future cites
log(patent stock)	0.104***	0.182***	0.212***	0.278***	0.307***	0.207***	0.352***
	(0.008)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.014)
R&D	0.163***	0.246***	0.281***	0.364***	0.367***	0.144***	0.652***
	(0.032)	(0.046)	(0.049)	(0.066)	(0.060)	(0.029)	(0.152)
log(age)	-0.031***	-0.065***	-0.073***	-0.100***	-0.103***	-0.085***	-0.201***
	(0.007)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.017)
log(total assets)	0.027***	0.055***	0.059***	0.087***	0.099***	0.067***	0.104***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.011)
Exploit	-0.072***	-0.042**	0.005	0.225***	0.292***	-0.189***	1.129***
	(0.014)	(0.020)	(0.021)	(0.022)	(0.021)	(0.019)	(0.033)
Explore	0.009*	0.017**	0.036***	0.093***	0.148***	0.003	0.441***
	(0.005)	(0.008)	(0.009)	(0.011)	(0.012)	(0.007)	(0.024)
Exploit + Explore	0.112***	0.319***	0.468***	0.884***	1.018***	0.078***	2.069***
	(0.017)	(0.023)	(0.024)	(0.026)	(0.025)	(0.022)	(0.037)
Time + Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	24163	24163	24163	24163	24163	24163	24163
R^2	0.323	0.489	0.550	0.686	0.739	0.520	0.668

Table 7 - Patent citation distribution break out

Notes: This tables presents OLS regression results. All dependent variables are log-transformed. Top 1% are the number of patents that fall into the 1% most cited patents within a given 3-digit technology class and application year. Top 5% to 2% are the number of patents that fall into the 5% to 2% most cited patents within a given 3-digit technology class and application year. Top 10% to 6% are the number of patents that fall into the 10% to 6% most cited patents within a given 3-digit technology class and application year. Top 10% to 6% are the number of patents that fall into the 10% to 6% most cited patents within a given 3-digit technology class and application year. Top 25% to 11% are the number of patents that fall into the 25% to 11% most cited patents within a given 3-digit technology class and application year. Top 50% to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You can be solved to 26% most cited patents within a given 3-digit technology class and application year. You cite' are the number of patents that fall into the



	а	b	
Dependent variable	Capital	Labor	
	Productivity	Productivity	
log(patent stock) _{I-1}	0.011	0.017**	
	(0.007)	(0.007)	
R&D t-1	-0.957***	-0.639***	
	(0.081)	(0.106)	
log(age) t-1	-0.048***	0.086***	
	(0.010)	(0.011)	
log(total assets) r-1		0.935***	
		(0.008)	
log(employees) _{f-1}	0.987***		
	(0.008)		
Exploit t-1	0.005	-0.054**	
	(0.018)	(0.022)	
Explore r-1	0.048***	0.049***	
	(0.013)	(0.015)	
Exploit + Explore t-1	0.123***	0.045**	
	(0.020)	(0.022)	
Time + Industry FE	Yes	Yes	
N	20707	20707	
R ²	0.943	0.917	

Table 8 – Performance regressions

Notes: This tables presents OLS regression results. All dependent variables are log-transformed and winsorized by year at the 1% level. Patent stock are all eventually granted patents applied for up to year t-1. R&D is R&D expenditures scaled by total assets. Age is years since IPO. 'Exploit'/'Explore' indicates all firms focusing on exploitation/ exploration, as classified by the PCA shown above. 'Exploit+Explore' indicates all firms that score high (>median) on both components. All categories are mutually exclusive. Time fixed effects are 23 dummies for each year. Industry fixed effects are 25 dummies for each 2-digit-SIC industry. All models include an intercept which is omitted in the table. Standard errors clustered at the firm level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

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	а	b	c	d
Dependent variable	Entry 0/1	Log(No. Entries)	log(new sales)	Prod. Proximity
log(patent stock) _{f-1}	-0.002	0.000	0.034	-0.010***
	(0.013)	(0.004)	(0.024)	(0.003)
R&D _{t-1}	-0.073	0.007	0.341***	0.222***
	(0.146)	(0.021)	(0.077)	(0.025)
log(age) t-l	-0.025	-0.011**	-0.070**	-0.025***
	(0.020)	(0.005)	(0.030)	(0.004)
log(total assets) :-1	0.103***	0.030***	0.312***	0.007***
	(0.013)	(0.003)	(0.020)	(0.003)
Exploit r-1	-0.090**	-0.024***	-0.187***	0.038***
	(0.039)	(0.008)	(0.048)	(0.008)
Explore r-1	0.095***	0.019***	0.061*	-0.009*
	(0.032)	(0.007)	(0.035)	(0.006)
Exploit + Explore t-1	0.070*	0.008	0.050	0.024***
-	(0.042)	(0.010)	(0.063)	(0.008)
Time + Industry FE	Yes	Yes	Yes	Yes
Ν	2287	2287	2287	5800
R ²		0.118	0.173	0.346

Table 9 – Market Entry and Product Proximity Regressions

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Notes: All dependent variables are measured in t+1 to t+3. Model (a) is a Probit model where the dependent variable indicates if a given firm enters at least one new product market, defined as the first time appearance of positive sales in a given 3-digit SIC industry where the firm has not generated sales previously. Model (b) is an OLS regression of the logarithm of (no. entries + 1). Model (c) is an OLS regression of the logarithm of (no. entries + 1). Model (c) is an OLS regression of the logarithm of (new sales +1), where new sales is the total amount of sales generated in all new industries. Model (d) is an OLS regression of product proximity based on textual analysis of firms' 10k fillings by Hoberg and Phillips (2015, 2010), multiplied by 100 to give it a proportional value. Patent stock is the cumulative number of patents applied for since 1976. 'Exploit'/Explore' indicates all firms focusing on exploitation/ exploration, as classified by the PCA shown above. 'Exploit+Explore' indicates all firms that score high (>median) on both components. All categories are mutually exclusive. All models include an intercept which is omitted in the table. Heteroscedasticity-robust standard errors are clustered at the firm level and shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.



Innovation Over the Business Cycle





Innovation Over the Business Cycle





Exploration/Exploitation over the Business Cycle































Extensive or Intensive Margins?

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Extensive or Intensive Margins?

Inventor Tenure over the Business Cycle

Relation with GDP Growth

•Explore

	a	b	С
	GDP Growth t+1	GDP Growth t+2	GDP Growth t+3
Explore PCA Score	5.258***	3.733***	3.253***
-	(1.061)	(0.825)	(1.024)
N	25	25	25
r2	0.550	0.419	0.357

•Exploit

	а	b	с
	GDP Growth t+1	GDP Growth t+2	GDP Growth t+3
Exploit PCA Score	-4.608***	-3.271***	-2.254**
	(1.142)	(1.073)	(1.056)
N	25	25	25
r2	0.472	0.360	0.191

A Non-Patent Related Measure of Exploration

Summary

- Puzzle: Innovation, as measured by R&D, is procyclical
- Model allowing different types of innovation –Exploration countercyclical; exploitation procyclical
- Metrics of firm level exploration/exploitation
 - PCA of readily available patent portfolio measures
- Exploration is countercyclical and exploitation is procyclical