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The impact of patenting on the size of high-tech firms: the role of venture capital and product market regulation

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Abstract We investigate how public policies related to product market regulation (PMR) influence the ability of European young venture-capital (VC) backed firms compared to a sample of matched non-VC backed firms to grow in size in proportion to their innovative activity. Whereas VCs can presumably offer value-added services to overcome the regulatory constraints of PMR, we find that VC-backed firms relative to non-VC backed ones are more adversely sensitive to these policies. This evidence indicates that PMR impedes the most VC-backed firms' high-potential for innovation-driven growth.

Keywords Venture capital · Product market regulation · Innovation · High-tech ventures · Public policy

JEL Classification G28 Government Policy and Regulation · G24 Investment Banking • Venture Capital • Brokerage • Ratings and Ratings Agencies

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1 Introduction

The innovation economics literature suggests that returns to innovation depend on the ability of innovating firms to attract the complementary resources they need to exploit commercially their innovative knowledge (Teece 1986). Hence, the ease with which these resources are accessible to innovative firms is extremely important and is partly a function of the public policy and the regulatory environment (Restuccia and Rogerson 2008; Arnold et al. 2011; Bartelsman et al. 2013). This is so because research indicates that flows of labor and capital resources to patenting firms across countries depend on regulations governing product and labor markets (Andrews et al. 2014). Given the potential role of public policy to influence the ability of national economies to reallocate resources towards innovative firms over time and to facilitate commercialization of new ideas, this paper builds on prior work of Andrews et al. (2014) and investigate the extent to which product market regulations (PMR) influence the ability of young firms to grow in size in proportion to their patenting activity. Patenting firms grow in size (Balasubramanian and Sivadasan 2011), but they are less able to do so in a policy unfriendly environment (Andrews et al. 2014).

The unresolved question remains whether young and innovative firms can devise strategies to overcome regulations that make competition more difficult and impede their innovation-driven growth. This question deserves attention because young firms are more sensitive to these regulatory burdens compared to old firms (Andrews et al. 2014) and are viewed as an important contributor to job creation and economic growth (Haltiwanger et al. 2013; Criscuolo et al. 2014). In this paper, we ask whether obtaining resources from venture capital (VC) investors offers a counter-force and thus, a possible strategic solution to innovative firms to overcome growth-related impediments from PMR.

VC investors not only provide substantial financial resources to their portfolio firms; but they also coach portfolio firms in areas where these firms lack expertise (e.g., Gorman and Sahlman 1989), and provide quality signals (Megginson and Weiss 1991) and business contacts to portfolio firms, making it easier for them to obtain additional resources. Whereas research indicates that VC-backing has a positive effect on firms' performance in terms of innovation (Kortum and Lerner 2000), growth (Puri and Zarutskie 2012), productivity (Chemmanur et al. 2011; Croce et al. 2013), and the likelihood of going public (Chemmanur et al. 2010; Puri and Zarutskie 2012; Cumming et al. 2014), it is to the best of our knowledge unexplored whether VC-backed firms are less affected compared to non-VC-backed firms by PMR.

Whether VC-backed firms are better able to cope with regulatory burdens of PMR in attracting resources to grow in proportion to their innovation activity is not as straightforward as one might assume. As noted above, the support provided by VC investors to portfolio firms in attracting valuable resources may also help them overcome policy and regulatory constraints. However, VC-backed firms have also the greatest growth potential and therefore they might suffer disproportionately from these constraints. Indirect evidence in line with this latter argument comes from studies inspired by institutional theory according to which related differences across countries in the functioning of the VC market is tied to the existence of an unfavorable policy and regulatory environment (e.g., Bruton et al. 2005; Armour and Cumming 2006).

In line with our research question, we explore the moderating role of PMR in the realization of returns to innovation for VC-backed firms. We focus on the country-level regulations of product market because stringent PMR raise the costs of inputs and/or lower the quality of these inputs for firms (Arnold et al. 2011). These regulations also are likely to increase the failure costs associated with experimentation of new technologies by young high-tech firms, and reduce the returns to innovation. In turn, these higher costs influence the propensity of young high-tech firms to invest in the development of high risk, radical innovations and put constraints on their ability to exploit the business opportunities potentially created by their innovation activity. There are a few noteworthy remarks with respect to our operationalization of this research question. First, we analyze the sensitivity of firm size to the patent stock as moderated by PMR, and firm size represents total assets or sales. Second, we compare a sample of VC-backed firms with a matched sample composed of twin non-VC-backed firms. Third, we also perform a fine-grained analysis of indicators of PMR, distinguishing the effects of restriction to competition through barriers to trade and international investment (hereafter, BTI), barriers to entrepreneurship (hereafter, BTE), and the extent of state control of enterprises (STC).

Data for this analysis are obtained from the VICO database, a large-scale longitudinal dataset on young high-tech firms located in seven European countries that was created by the 7th FP VICO project (http://www.vicoproject.org/). Results of our econometric estimates show that both VC-backed and non-VC-backed young high-tech firms suffer from a regulatory environment that hinders competition. There is a decrease of the sensitivity of sales and total assets to the patent stock with increasing product market regulatory burdens for both set of firms; the magnitude of this negative effect is stronger for VC-backed firms relative to the control sample of non-VC-backed firms. More specifically, we show that stringent regulations are more disruptive for VC-backed firms' growth in sales and total assets in all dimensions of PMR except BTI. Our results confirm that PMR policies can disproportionally affect those firms with the highest potential for growth. Therefore, we recommend lenient PMR policies, as regards notably BTE and STC.

2 Methods

2.1 Data and sample

We use data on VC investments from the VICO database. The VICO database contains longitudinal data on 8346 firms that are located in seven European countries—Belgium, Finland, France, Germany, Italy, Spain, and the United Kingdom, were less than 25 years old in 2010, were independent at their founding date (i.e., not controlled by other business organizations), operate in high-tech manufacturing and services industries, and are observed between 1994 and 2009. Out of these firms, 758 are VC-backed.[1]

The sample of VC-backed firms is a representative sample of the firms in the abovementioned countries during the period between 1994 and 2009. The sample of VC-backed firms comes from a random draw of several commercial databases (i.e., Thomson One, VC-Pro, and Zephyr) and the following country-specific databases: the Research on Entrepreneurship in Advanced Technologies (RITA) directory and Private Equity Monitor for Italy, the ZEW Foundation Panel for Germany, the Library House (now Venture Source) for the UK, the yearbooks of the Belgian Venture Capital & Private Equity Association and the Finnish Venture Capital Association, and the WEBcapitalriesgo database for Spain. After cross-checking this information with publicly available information from the ventures' and investors' websites and press releases, we applied several filters to include these firms into our sample. First, the initial injection of VC capital had to be between 1994 and 2004. Second, the firms must have been less than 10 years old at the time of the first injection of VC capital. We also exclude investments such as leveraged buyouts, real estate, distressed buyouts, and other private equity investments from our sample. For all VC-backed firms, the VICO database provides information on the VC investment rounds (i.e., the date of the round, the investment amount, and the identity of VC investors) between 1994 and 2009. The non-VC-backed companies were randomly extracted from all available vintage years of Bureau van Dijk's Amadeus database. Also in this case, country-specific proprietary sources (e.g., Creditreform in Germany) were used to complete the dataset. For both VC-backed and non-VC-backed firms, further information is available, including the sectors of operation of the ventures, their addresses, patenting data from the European Patent Office, and longitudinal accounting data insourced from the Bureau Van Dijk Amadeus database.

To address concerns of survivorship bias, VICO database includes both surviving and non-surviving ventures. By the end of the observation period, surviving firms may have either gone through an IPO or remained privately held and independent. Non-surviving firms may have been acquired, thereby losing their independence, may have gone bankrupt or may have otherwise terminated operations.

In this study we only include the 369 firms that received their first round of financing from at least one independent VC (IVC). Of these VC-backed firms, 62 operate in biotechnology, 71 in information and communication technology manufacturing and other high-tech manufacturing, and 236 in software, Internet, telecommunication, and other high-tech services. We focus here on IVC and do not consider ventures backed (only) by captive VC investors such as corporate, bank affiliated, and governmental VC, for the following two reasons. First, IVCs

[1] Several previous studies have used the VICO database to analyze the impact of VC investments on firms' innovation (Bertoni and Tykvová 2015), growth (Colombo et al. 2014; Grilli and Murtinu 2014, 2015), productivity (e.g., Croce et al. 2013; Colombo and Murtinu 2016), likelihood of going public (Cumming et al. 2014) and other performance measure (e.g. participation of firms in research projects funded by the European Commission, (Colombo et al. 2012, 2016). For a detailed description of the VICO database, see Bertoni and Martí (Bertoni and Martí 2011).

quite uniformly are the most diffused and prevalent type of VC across the home countries of the ventures included in our sample, while diffusion of other types of VC investors is strongly influenced by country-specific factors and substantially differs from one country to another (Mayer et al. 2005). Second, previous studies have highlighted that captive investors have strategic objectives in addition to financial objectives.[2] Moreover, portfolio companies backed by captive investors can leverage the resources and capabilities of the investors' parent companies. This especially applies to corporate VC (Dushnitsky 2012; Alvarez-Garrido and Dushnitsky 2015). The different objectives, resources, and investment strategies of different types of VC might be a source of unobserved heterogeneity.

We build a sample of non-VC-backed firms which is comparable to the sample of VC-backed firms according to an a priori defined set of characteristics. Our goal is to match every VC-backed firm with a twin non-VC-backed firm based on characteristics observed in the year of first financing (for a similar procedure in the VC literature, see e.g. Brau et al. 2004; Chemmanur et al. 2011; Engel and Keilbach 2007; Jain and Kini 1995; Megginson and Weiss 1991; Puri and Zarutskie 2012; Croce et al. 2013). The rationale for matching is the fact that VC-backed firms may differ from non-VC-backed firms along dimensions that may influence the size-to-patent elasticity, generating a bias in our analysis. Selection of a control group using a matching estimator allows us to control at least for observed heterogeneity between VC-backed firms (i.e., treatment observations) and non-VC-backed firms (i.e., control observations). For this purpose, we use a propensity score matching. For each VC-backed firm in the year of receipt of VC financing (t), we find the firm that exhibits the closest probability of receiving VC in year t (i.e., the most similar propensity score) but did not receive VC. More specifically, the estimated propensity score is obtained from a probit model with the dependent variable that equals 0 for control observations and 1 for treatment observations. The independent variables include firm age and firm patent stock. After matching, we only use the observations for years after t to test our hypothesis and eliminate observation-years prior to t for both the sample of VC backed firms and non-VC backed firms.

We chose to analyze separately in the VC-backed and control samples the moderating effect of indicators capturing the characteristics of the regulatory environment on the relationship between patent stock and firm size. Across each group, we estimate a fixed-effect panel data model (with robust standard errors) since Hausman tests recommends the use of fixed effect rather than random effect models.

[2] For instance, corporate VC investors generally have the objective to open a "technology window" on the promising new technologies developed by portfolio companies (see e.g. Siegel et al. 1988; Ernst et al. 2005; Dushnitsky and Lenox 2005; Benson and Ziedonis 2009), while bank VC investors aim at generating additional demand for the commercial and investment bank services provided by their parent company (Hellmann et al. 2008). For an anlysis of the pattern of investment of different VC types, see Bertoni et al. (2015).

2.2 Measures

2.2.1 Dependent variables

We have two dependent variables that reflect firm size: *Total assets* and *Sales.* These measures are both expressed in thousand Euros adjusted for inflation (in 2005 Euro).

2.2.2 Independent variables

Patent stock, our key dependent variable, represents the technological assets of firms and is calculated as follows. We first calculated the number of annual successful (i.e., granted) patent applications of each firm in the European Patent Office, dated at the application year. Then, we applied a 15 percent knowledge-depreciation rate (Hall et al. 2005) to generate the patent stock. We added one to this variable and took the logarithm to address skewness.

PMR represents the OECD product market regulation index. This indicator measures the degree to which policies, regulations, and other governmental interventions create an environment that promotes or hinders competition in the product market. More specifically, PMR reflects economy-wide regulations in each country in the following areas: state control of business enterprises (*STC*), legal and administrative barriers to entrepreneurship (*BTE*), and finally, barriers to international trade and investment (*BTI*). The tree structure of the PMR indicator set is presented in Fig. 1 and we have included the values for these components in Table A1 across countries of our sample. There is substantial variation of these measures across time and countries. It is noteworthy to mention that for years prior to 1998 when these variables were not collected by OECD, we back-fill the data using the values of the year 1998.

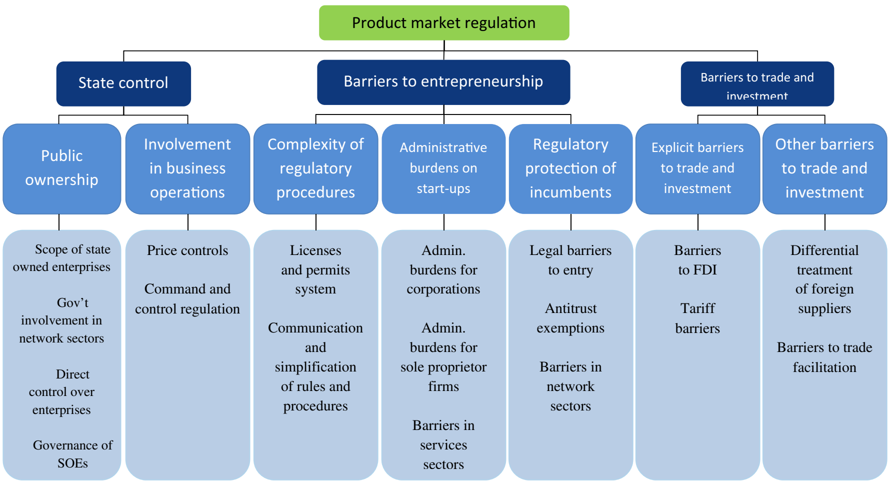

Fig. 1 Scheme of OECD product market regulation indicators (source. http://www.oecd.org/eco/growth/reducing-regulatory-barriers-to-competition-2014.pdf)

Table 1 Two-sample *t* test of the year of matching for first receipt of independent VC and matched control group

Panel (A)	VC-backed sample		Matched control group		
	Number of firms	Mean of patent stock[a]	Number of firms	Mean of patent stock[a]	Difference
Biotech	62	0.561	62	0.316	−0.245
ICT	71	0.467	71	0.481	0.014
Software and TLC	236	0.089	236	0.076	−0.013
Panel (B)	**Number of firms**	**Mean of age**	**Number of firms**	**Mean of age**	**Difference**
Biotech	62	1.355	62	1.129	−0.226
ICT	71	3.338	71	3.310	−0.028
Software and TLC	236	2.373	236	2.352	−0.021

[a] The variable is logged

Table 2 Descriptive statistics and correlation matrix for VC-backed firms (Panel A) and a control group of non-VC-backed firms (Panel B)

Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel (A)									
1. Sales[a]	7.09	2.31	–						
2. Total assets[a]	7.54	1.89	0.621	–					
3. Patent stock[a]	0.16	0.36	−0.041	0.157	–				
4. Age[a]	1.90	0.66	0.314	0.101	−0.031	–			
5. PMR	1.63	0.40	−0.075	0.158	−0.040	−0.408	–		
6. BTI	0.49	0.24	−0.065	0.106	0.018	−0.361	0.700	–	
7. BTE	2.13	0.47	−0.004	0.097	−0.010	−0.460	0.830	0.594	–
8. STC	2.26	0.72	−0.098	0.169	−0.066	−0.263	0.898	0.451	0.540
Panel (B)									
1. Sale[a]	6.22	2.18	–						
2. Total assets [a]	6.01	2.21	0.815	–					
3. Patent stock[a]	0.07	0.29	0.150	0.319	–				
4. Age[a]	1.92	0.67	0.137	0.087	−0.019	–			
5. PMR	1.63	0.40	−0.102	−0.060	0.008	−0.380	–		
6. BTI	0.48	0.23	−0.056	−0.101	−0.055	−0.368	0.688	–	
7. BTE	2.15	0.47	0.000	−0.004	0.025	−0.426	0.846	0.591	–
8. STC	2.27	0.72	−0.148	−0.074	0.014	−0.244	0.907	0.449	0.581

[a] The variable is logged to reduce skewness

We also control for the age of firms (in years) and after adding one to this variable, we log it for skewness concerns (*Age*). It is again important to mention that our estimates include firm fixed effects that will control for unobserved time-invariant heterogeneity.

Table 3 Fixed effect panel data models of logged total assets

	VC-backed sample					Matched control sample				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
Patent stock[a]	0.447 (0.340)	2.262*** (0.709)	1.213* (0.641)	2.195*** (0.658)	1.851*** (0.546)	0.510 (0.371)	2.183*** (0.645)	1.989*** (0.487)	2.116*** (0.604)	1.923*** (0.664)
Age[a]	0.109 (0.106)	0.165 (0.118)	0.152 (0.112)	0.170 (0.124)	0.136 (0.108)	0.430*** (0.083)	0.374*** (0.096)	0.455*** (0.091)	0.403*** (0.097)	0.354*** (0.089)
PMR		0.310 (0.263)					−0.093 (0.168)			
PMR × patent stock		−1.127** (0.467)					−0.950*** (0.261)			
BTI			0.767 (0.861)					0.397 (0.466)		
BTI × patent stock			−1.714 (1.339)					−3.113*** (0.532)		
BTE				0.253 (0.201)					−0.009 (0.132)	
BTE × patent stock				−0.834** (0.351)					−0.644*** (0.200)	
STC					0.124 (0.126)					−0.116 (0.083)
STC × patent stock					−0.616** (0.243)					−0.616*** (0.206)
Constant	7.259*** (0.197)	6.648*** (0.557)	6.846*** (0.474)	6.610*** (0.573)	6.917*** (0.392)	5.139*** (0.165)	5.386*** (0.403)	4.906*** (0.317)	5.195*** (0.412)	5.551*** (0.305)
Observations	2301	2301	2301	2301	2301	2439	2439	2439	2439	2439
Firms	301	301	301	301	301	308	308	308	308	308

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

[a] The variable is logged. Robust standard errors are presented in parenthesis

Table 4 Fixed effect panel data models of logged sales

	VC-backed sample					Matched control sample				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
Patent stock[a]	0.017 (0.506)	2.292** (0.961)	0.287 (0.716)	1.860** (0.806)	2.413** (1.142)	0.502 (0.333)	1.507* (0.777)	1.492*** (0.526)	1.499* (0.772)	1.243* (0.700)
Age[a]	0.874*** (0.182)	1.262*** (0.184)	1.002*** (0.217)	1.329*** (0.180)	1.080*** (0.177)	0.359*** (0.102)	0.423*** (0.122)	0.475*** (0.117)	0.421*** (0.119)	0.371*** (0.116)
PMR		1.224*** (0.336)					0.218 (0.209)			
PMR × Patent stock		−1.313* (0.686)					−0.589 (0.439)			
BTI			1.397** (0.620)					1.195* (0.612)		
BTI × Patent stock			−0.537 (0.952)					−2.232** (0.902)		
BTE				1.028*** (0.292)					0.155 (0.163)	
BTE × Patent stock				−0.855** (0.430)					−0.412 (0.326)	
STC					0.513*** (0.183)					0.046 (0.106)
STC × Patent stock					−0.963* (0.548)					−0.332 (0.292)
Constant	5.466*** (0.336)	2.650*** (0.745)	4.505*** (0.654)	2.391*** (0.814)	3.817*** (0.589)	5.503*** (0.197)	5.020*** (0.510)	4.695*** (0.452)	5.045*** (0.507)	5.375*** (0.398)
Observations	2025	2025	2025	2025	2025	2283	2283	2283	2283	2283
Firms	335	335	335	335	335	345	345	345	345	345

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

[a] The variable is logged. Robust standard errors are presented in parenthesis

3 Results

Table 1 presents the outcome of the propensity score matching at t, the year of initial receipt of IVC for VC-backed firms. As the results of one-to-one matching suggest, the two samples in each industry do not show any significant difference in means of the patent stock and age variables (at conventional confidence levels) in the year of matching.

Table 2 shows the descriptive statistics and correlation matrix for each sub-sample. There is naturally high correlation between PMR and its component indicators (see Fig. 1); for this reason, we don't include two or more of these policy measures in one single regression to avoid multi-collinearity issues. The sales and total assets size variables are also correlated as one would expect and therefore, the results for these dependent variables should be qualitatively similar (Table 3).

Table 3 shows the results of fixed effect panel data regressions when the dependent variable is the log of total assets (log of sales). Each table has two panels; in the left side the results of VC-backed firms are presented in Models I–V, and in the right side, the results of the matched control sample of twin non-VC-backed ventures are presented in Model VI–X. The baseline models (i.e., Model I and Model V) suggest that the coefficient of *Patent stock* is not significant in either VC-backed or non-VC-backed firms. Furthermore, *Age* is positive and only significant for the sample of non-VC backed firms (Model VI, $p < 0.01$). Regarding the interaction terms, results of Model II and VII show negative and statistically significant interaction terms between *PMR* and *Patent stock* ($p < 0.05$, and $p < 0.01$

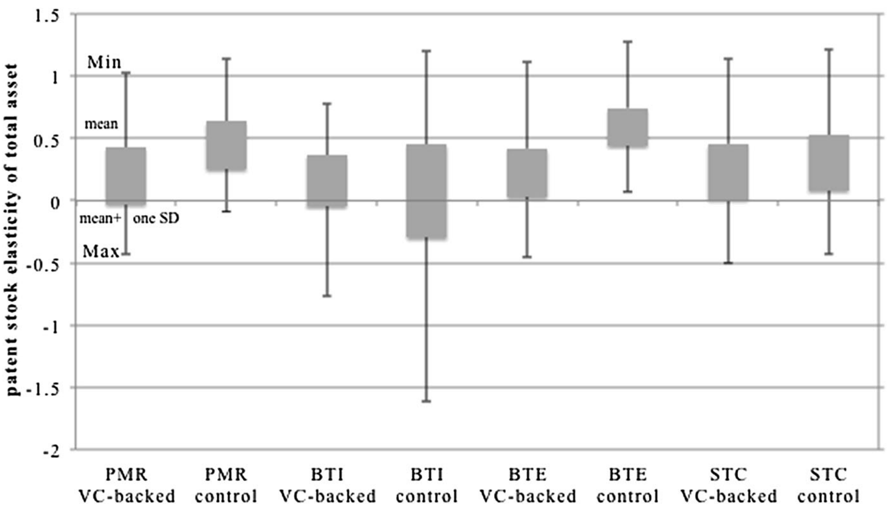

Fig. 2 Patent stock elasticity of total assets. For each indicator, the two samples of VC-backed ventures and control ventures are shown. For each sample, the plots show the patent stock elasticity of sales computed at four points of each regulatory indicator (whisker at the *top* show the minimum of policy indicator, whisker at the *bottom* show the maximum of policy indicator, and the *box* goes down from the mean of indicator variable to one standard deviation above the mean

respectively for each model). This is consistent with our theoretical predictions that the positive association between patenting and the size of VC-backed firms progressively vanishes as regulatory constraints increase. Models III–V present the interaction terms between *BTE*, *BTI*, *STC*, and *Patent stock* for VC-backed firms. Except for *BTI*, the interaction terms are negative and significant ($p < 0.05$). As regards the matched control sample, the results of interaction terms between *BTE*, *BTI*, *STC*, and *Patent stock* in Model VII–X are negative (all, $p < 0.01$). It is noteworthy to mention that the results are based on a fixed-effect model, meaning that the effect of PMR is due to its change over time in the country of the firm.

Table 4 presents the same set of regressions with logged sales as dependent variable. Results are similar to those illustrated above. Models I and VI report the baseline results. The coefficient of *Patent stock* is positive and non-significant; the coefficient of *Age* is positive and significant ($p < 0.01$). As regards the sample of VC-backed firms, the results of interaction terms are presented in Model II–V. The interaction term of *Patent stock* and *PMR* is negative ($p < 0.1$). The interaction terms between *Patent stock* and *BTI*, *BTE*, and *STC* are negative (respectively, n.s., $p < 0.05$, $p < 0.1$). Models VI–X of Table 4 present the regressions predicting the sales for the matched control sample. As regards the sample of non VC-backed firms, the results of interaction terms are presented in Model VII–X. The interaction term of *Patent stock* and *PMR* is negative (n.s.). The interaction terms between *Patent stock* and *BTI*, *BTE*, and *STC* are negative (respectively, $p < 0.05$, n.s., n.s.). In general, these findings are consistent with Andrews et al. (2014) and confirm the view that PMR negatively affect the innovation-driven growth of young high-tech

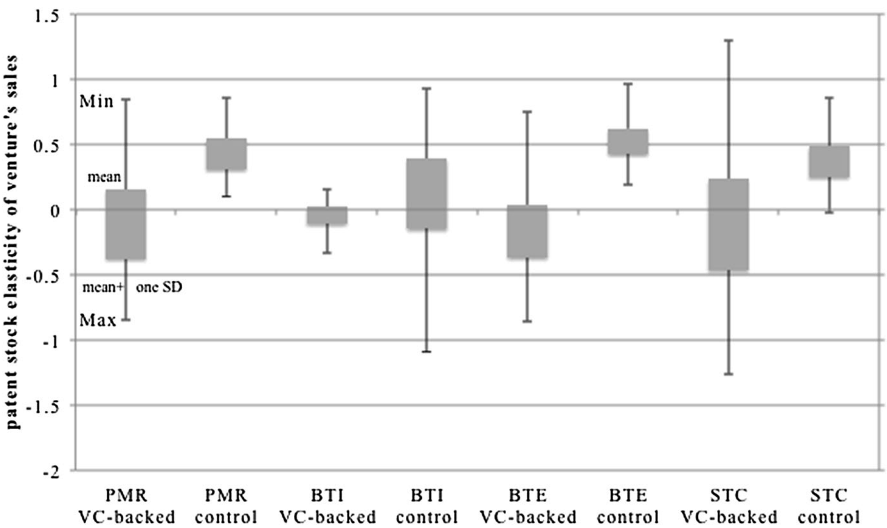

Fig. 3 Patent stock elasticity of sales. For each indicator, the two samples of VC-backed ventures and control ventures are shown. For each sample, the plots show the patent stock elasticity of sales computed at four points of each regulatory indicator (whisker at the *top* show the minimum of policy indicator, whisker at the *bottom* show the maximum of policy indicator, and the *box* goes down from the mean of indicator variable to one standard deviation above the mean

Table 5 Fixed effect instrumental variable panel data models of logged total assets

	VC-backed sample					Matched control sample				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
Patent stock[a]	0.626***	2.318***	1.144*	2.068***	2.098***	0.515**	1.060**	0.748	0.912*	1.126**
	(0.233)	(0.710)	(0.645)	(0.763)	(0.666)	(0.208)	(0.533)	(0.641)	(0.497)	(0.523)
Age[a]	0.077	0.108	0.107	0.104	0.094	0.390***	0.313***	0.395***	0.346***	0.301***
	(0.061)	(0.077)	(0.066)	(0.080)	(0.070)	(0.047)	(0.064)	(0.055)	(0.064)	(0.058)
PMR		0.247					−0.175			
		(0.158)					(0.107)			
PMR × patent stock		−1.123***					−0.347			
		(0.435)					(0.341)			
BTI			0.541					0.073		
			(0.500)					(0.280)		
BTI × patent stock			−1.262					−0.535		
			(1.528)					(1.482)		
BTE				0.174					−0.072	
				(0.125)					(0.081)	
BTE × patent stock				−0.729**					−0.177	
				(0.351)					(0.211)	
STC					0.119					−0.148**
					(0.083)					(0.058)
STC × patent stock					−0.693**					−0.302
					(0.282)					(0.257)
Observations	2243	2243	2243	2243	2243	2388	2388	2388	2388	2388
Firms	295	295	295	295	295	302	302	302	302	302
Under-identification	80.591***	9.200***	13.103***	10.302***	8.609**	32.530***	9.451***	12.297***	7.615***	9.478***
Weak identification	140.371	34.051	8.310	14.376	12.628	133.466	9.025	11.612	38.659	6.969
Hansen J statistic	0.789	0.006	0.562	0.040	0.048	1.963	2.280	2.366	2.245	2.033

Table 5 continued

	VC-backed sample					Matched control sample				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
Chi-sq P value of over-identification	0.374	0.939	0.454	0.841	0.827	0.161	0.131	0.124	0.134	0.154

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

[a] The variable is logged. Robust standard errors are presented in parenthesis

companies. This applies to both VC-backed and non-VC-backed firms; however, the extent of this negative effect is larger for VC-backed firms.

To better assess differences between these two categories of firms, we plot the estimated size-to-patent stock elasticity contingent on the values of the PMR variables. Figure 2 presents the patent stock elasticity of total assets, while in Fig. 3 we consider the sales-to-patent stock elasticity. For each PMR indicator, we compare the sample of VC-backed firms with the control sample.

The first column in Fig. 2 shows that when the PMR index increases from the minimum to the maximum, the estimated total assets-to-patent stock elasticity of VC-backed firms decreases 145 percentage points (from 104 to −43 %). The corresponding drop for non-VC-backed firms is considerably smaller (122 percentage points). A similar pattern applies to the BTE index. For the VC-backed firms, the decrease of the total assets-to-patent stock elasticity when the BTE index varies from the minimum to the maximum is 1.29 time larger than the corresponding drop for non-VC-backed firms. Conversely, the decrease of the elasticity generated by an increase of the STC index is similar for VC-backed and non-VC-backed firms (i.e., equal to 162 percentage points), while the effect of the (decreasing) variation of the BTI is much larger for non-VC-backed firms (i.e., equal to 281 percentage points) than for VC-backed ones (i.e., 155 percentage points).

Turning attention to Fig. 3, the pattern of variation is very similar, except that the differences between VC-backed and non-VC-backed firms in the sensitivity of the sales-to-patent elasticity to variations of the indicators reflecting the extent of PMR, are larger than those illustrated above in the total assets-to-patent stock elasticity. For example, when the PMR index varies from the minimum to the maximum the estimated sales-to-patent stock elasticity of VC-backed firms declines from 85 to −84 %, a drop of 169 percentage points. For the control group composed of non-VC-backed firms the drop is equal to 76 percentage points. A similar pattern is observed for the BTE and STC index. The drop of the estimated elasticity value for VC-backed firms respectively is 2.07 and 2.89 times larger than for non-VC-backed firms. Again, the only exception is the BTI index, which generates a larger drop in the estimated elasticity for non-VC-backed firms compared to VC-backed firms (i.e., 4.16).

Endogeneity To address potential concerns of endogeneity regarding firm's patenting activity arising from unobserved heterogeneity, we use an instrumental variable approach. Following Andrews et al. (2014), we build an instrument related to litigation propensity. More precisely, the index measures the share of patents of the firm's patent portfolio in each 4-digit IPC class k multiplied by the normalized number of all patents litigated in a given year in that class k. We obtain litigation information found in Thomson Innovation, which is provided by Westlaw, a Thomson Reuters company. We use the lag of patent stock as an additional instrument with the assumption that errors are not serially correlated (Angrist and Krueger, 2001). Furthermore, in the regressions in which we include the interaction term of *PMR* variables and *Patent stock*, we add the instrumental variable obtained from multiplying the litigation propensity and the corresponding PMR variable. The regression results obtained from xtivreg2 in Stata (Schaffer 2012) are presented in Table 5 (for *Total assets* only).

We did a series of tests to investigate the relevance and validity of instruments. Tests of under-identification suggest that models are identified, and hence the instruments are relevant. Regarding weak identification, we perform Kleibergen–Paap Wald F-statistic, which shows values higher than the Stock–Yogo IV critical threshold of 15 %, indicating that instruments are strongly correlated with the endogenous regressors. Finally, the over-identification tests of Hansen's J statistic show that we cannot reject the validity of instruments, suggesting that instruments are uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.

We observe a positive and significant correlation between the litigation propensity measure and firms' patent stock (for the sake of synthesis, results of the first-stage regressions are not reported in the text, but they are available from the authors upon request). There could be two plausible explanations. First, litigation is particularly frequent in new technology areas (Lanjouw and Schankerman 1997). Then, the positive correlation between patent stock and litigation propensity would suggest that new young firms are likely to focus their innovative effort in new technology areas in which there is greater market potential for exploitation. Indirect evidence supporting this view is offered by previous studies that showed that young high-tech firms have a competitive advantage to realize innovations that are radical rather than incremental (Henderson 1993; Tushman and Anderson 1986; Schneider and Veugelers 2010). Second, the opportunity costs of filing and maintaining patents are higher for young firms than older firms. Therefore, young firms that are resource-constrained would be more likely to patent only their most valuable inventions. Litigation is viewed as a proxy for patent value because only valuable patents are worth the costs of litigation (e.g., Harhoff et al. 2003). Then we again expect that young high-tech firms invest their scarce resources in technological areas in which their innovations can generate the most value and litigation propensity is higher.

Table 5 presents the second-stage results from the IV regressions. They are qualitatively similar to the ones presented earlier.[3] It is worth noting that the coefficient of *Patent stock* becomes positive and significant in baseline models of I and VI. As to the interaction terms, they are negative and significant in the VC-backed sample, with the exception of *BTI*. Conversely, in the control sample, the interaction terms are not significant, even though they have the expected negative sign.

We perform a series of robustness tests. First, we include squared term of *Age* in the regressions and obtain similar results. Second, we include year dummies to control for time-trends and obtain similar results. Third, to control for productivity, we construct an additional variable of sales minus pay-roll expenses divided by sales; despite a smaller sample size arising from missing pay-roll expenses, our

[3] We don't present the results from instrumental variable fixed effect panel models with the total sales as dependent variable because the instruments fail to pass weak identification tests. These results are available from authors upon request.

results remain similar. Fourth, because we do not test whether there is a statistically significant difference across coefficients of the groups of VC-backed and non-VC backed firms, in a new analysis we refrain from splitting the sample of VC-backed and non-VC backed firms. We insert a dummy variable indicating whether a firm is VC-backed or not. We run a fixed effect panel data model with three-way interactions terms between policy variables, patent stock, and VC-backing status. The results support our previous conclusions; for VC-backed firms the negative moderating effect of policy variables is always negative and significant (with the exception of the BTI variable).

4 Conclusion

In this paper we analyzed whether the different extent of product market regulations in different countries influences the elasticity of firm size to patenting for two categories of young high-tech firms: VC-backed and non-VC-backed firms. For this purpose, we have taken advantage of longitudinal accounting and patenting data on young high-tech firms located in seven European countries provided by the VICO dataset. We used a sample composed of 361 European VC-backed young high-tech firms and a sample of twin non-VC-backed firms. The results of our econometric estimates confirm the view that young high-tech firms are considerably and negatively affected by product market regulations. More interestingly, our findings document that VC-backed firms, which have the greatest growth potential (Croce et al. 2013), suffer more from regulatory constraints than their non-VC-backed counterparts, with the only exception of barriers to trade and foreign investments. These results pose serious concerns to policy makers, as previous studies have shown that these firms are fundamental for job creation (Haltiwanger et al. 2013; Criscuolo et al. 2014) and for the long-term growth of the economy.

This study contributes to several streams of research. First, we complement the literature on resource misallocation (Hsieh and Klenow 2009; Andrews and Cingano 2014) by focusing on the consequences of regulations and public policy interventions for a particular set of firms—young high-tech firms, which are the most in need of rapid allocation of resources to realize the economic potential of their innovation activity. Our results not only confirm the limited evidence on this category of firms provided by previous studies (Andrews et al. 2014), but they also go a step further by showing that the adverse consequences of stringent product market regulations are exacerbated for VC-backed firms, that is the firms that have the highest potential for growth. Second, we contribute to the stream of literature that focuses on the consequences of regulations and institutional environment for the functioning of VC markets (e.g., Bruton et al. 2005; Armour and Cumming 2006; Li and Zahra 2012). Factors that impede the well-functioning of VC market include (a) less developed stock markets (Black and Gilson 1998; Jeng and Wells 2000), (b) legal systems (Cumming et al. 2010) as regards notably a low level of investor protection (La Porta et al. 2000) and bankruptcy laws which favor lenders over equity holders (Armour and Cumming 2006), and regulatory constraints such as those arising from rigid labor market regulations (Jeng and Wells 2000). We additionally document that product market regulations by increasing barriers to competition negatively influence VC-backed firms, as they reduce the ability of these firms to benefit from their innovation activity and grow rapidly in size. As a corollary, the returns to VC investments are likely to be lower in countries with stringent product market regulations. This cursory observation in turn reflects the limited attraction that VC investors exhibit for this type of countries.

We are limited in a number of dimensions that would be interesting avenues for further research. The most important of these limitations is the lack of empirical methodology that establishes causality as regards the impact of product market regulations on the returns to innovation. Our approach could suffer from unobserved heterogeneities correlated with policy indicators across countries. A suggestion to overcome some of these concerns would be to exploit exogenous change related to policy reforms concerning product market regulations. We encourage further research in this direction in order to improve the stock of our knowledge on institutional variables that influence returns to innovation. Furthermore, future research can benefit from industry-level policy measures of product market regulation rather than country-level aggregate constructs. Finally, analysis of dependent variables related to growth rate of sales and total assets can be endeavors worth the future research.

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