Innovation and Learning during the Crisis: Evidence from firm level data for Eastern European countries[1]

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Abstract

The "creative destruction" process, intensified during economic downturns, is an important driver of productivity growth. The current downturn, however, due to its synchronized nature and association with a deep financial crisis, is unusually severe. Could this "Great Recession" adversely affect firms which could lead productivity growth in a context of normal business cycle? In this paper, we focus our analysis on the impact of the crisis on innovation and learning, two important sources of productivity growth. We apply panel data estimators and Juhn-Murphy Pierce decomposition technique to a unique firm-level dataset – composed by information from 3,363 firms in seven countries (Bulgaria, Hungary, Kazakhstan, Latvia, Lithuania, Romania, and Turkey) – for 2007, June 2009, January 2010 and June 2010 – in order to investigate the differential impact of the global economic crisis on sales performance of innovative (vs. no-innovative) and young (vs. older) firms in Eastern European countries. We found that the decline in sales growth of innovative and young firms was significantly larger when compared to no-innovative and older companies, respectively, even when controlling for different idiosyncratic firm characteristics, including financial conditions. These results were robust to the estimator applied. We also found that the premium for innovation and the ability of young firms to learn became increasingly negative during the crisis, suggesting that neither factors played a relevant role in innovative and young firms survival in those countries. We interpret these results as evidence that the crisis may not have a productivity-enhancing ("purgative") effect as other periods of economic downturn.

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1 - Introduction

The Schumpeterian view that recessions provide an opportunity for the economy to adjust through a "creative destruction" process is one of the most important conjectures to explain the fact that productivity is procyclical relative to output fluctuations. According to this view, economic crises are times of industrial renewal, when a purgative selection course takes place to eliminate less efficient firms while more dynamic ones emerge. Therefore, to the extent as continual changes in the composition of a population of firms are an important driver of productivity expansion, the "creative destruction" process, intensified during economic downturns, is an essential engine of long term economic growth.[2]

The current crisis, as pointed by IMF (2009), has two combined characteristics that make it unusually severe: it is highly synchronized across countries and is associated with a deep financial crisis, a rare combination in the postwar period. That is why many economists, as Reinhart and Rogoff (2008), and Romer (2009), look for parallels in the current crisis to the Great Depression of the 1930s.

Initially started in the U.S. housing market, the crisis spread rapidly across borders, after the collapse of Lehman Brothers in 2008, leading to a worldwide de-leveraging of financial markets. On the supply-side, the ultimate effects on the real economy were less access to credit, while on the demand-side the deterioration in the terms of trade has contracted the demand faced by export-oriented firms and their input providers. As a consequence, a large number of economies have fallen into recession: the global GDP growth rate has been reduced in 2009, with some regions, like Europe and Central Asia, being especially hit, with a 6.8 percent reduction in 2009 (World Bank (2010)).

Because of its extension and nature, the current crisis might be generating forces that weaken the dynamics of industrial renewal, and so the purgative selection might be adversely affecting firms that could lead productivity growth in a context of normal business cycle and credit conditions. In this context, two important sources of expansion in firm productivity must be highlighted: innovation and learning.

Innovative firms are expected to provide a positive contribution to economic growth, as innovation and R&D tend to be positively related to firm-productivity and sales performance

[2] For instance, in the 1930s, according to Field (2009), the American economy saw, after the Great Depression, impressive efficiency improvements, this was evidenced by an annual growth of total factor productivity of 2.31 percent.

(Aw, Roberts and Xu (2008)).[3] Empirical analysis in Eastern Europe for 2001-2004 shows that increasing innovation raises firm productivity growth, therefore increasing the speed of catching up with the technological frontier (World Bank (2008)). Conditional on size and survival rate, young firms are expected to grow faster than older firms, among other reasons, due to diminishing returns to learning (Klepper and Thompson (2007); Dunne, Roberts and Samuelson (1989)). In addition, young firms are often more productive than incumbents. For Eastern Europe and Former Soviet Union, World Bank (2008) shows evidence that in the early reformers group (EU10 plus Turkey), entrant firms that survive to market selection in technology advanced sectors tend to be more productive than the incumbents over time. The same study reports that in late reformers (most of Southeastern Europe and the CIS), the entry of new firms has contributed by about 10 percent to aggregate manufacturing productivity growth.

If innovation and learning are relevant drivers of firm productivity and economic growth, examining the differential impact of the crisis on young (vs old) and innovative (vs. no innovative) firms helps comprehend Eastern European growth prospects. For instance, if young companies have suffered more this could lead to a premature exit of young firms that would potentially be viable in another context, and – assuming the same firm entry rates of the pre-crisis period – the premature "aging" of the enterprise sector might soften market selection, therefore reducing productivity gains in the region. By the same token, if innovative firms have been more affected, this may hold back R&D investments, thus derailing the long term prospect for economic growth

Correa and Iootty (2010) tried to shed light on this matter while focusing on sales as a specific variable of real performance to be examined. Using a panel data of 1,686 firms (for 2007 and June 2009) - for six countries (Bulgaria, Hungary, Latvia, Lithuania, Romania and Turkey) they showed that innovative firms and young firms have been more affected by the crisis. In the present paper we update and refine (methodologically) that analysis using a broader and longer panel data (3,363 firms, now including Kazakhstan and for 2007, June 2009, January 2010 and June 2010), to continue the investigation on the differential impact of the crisis on sales growth of innovative (vs no innovative) and young (vs. old) firms in the Eastern Europe.

3 The micro-macro link between firm-level innovation theories of aggregate technological change and growth can be found in Klette and Kortum (2004).

We first apply panel-data estimators – within estimator and Hausman Taylor estimator (with and without propensity score matching) – in order to assess the crisis impact on sales growth performance of innovative and young companies, when controlling for firm characteristics. Second, we apply the Juhn-Murphy-Pierce technique to decompose the differences in sales growth performance within innovative vs. non-innovative firms (and young vs. old firms) into: i) differences in the distribution of observable characteristics (the characteristics effect); ii) differences in the "market value" of such characteristics (the returns effect); and iii) differences in unobservable attributes and "market values" (the unexplained effect).

Panel data analysis points to a set of results. First, it shows that the common impact of the crisis on sales growth performance of *all* firms was significantly negative, though in a decreasing rate. Second, when examining how innovative firms have been particularly affected, panel data analysis showed that they were more vulnerable to economic slowdown: the decline in sales growth of innovative firms was always (significantly) larger than the reduction experienced by non-innovative firms. This result was robust to the estimator applied. Third, panel data estimators also showed that sales growth performance of young firms was (significantly) more affected than older firms, a result that was robust to the estimator used.

From the Juhn-Murphy-Pierce method, when comparing innovative and non-innovative groups of firms, the results indicate that the premium to innovate decreased during the period. Second, for the young vs. older firm comparison, the JMP decomposition suggest that young firms are performing even worse since the crisis, and their (persistently) lower ability to learn might reinforce this negative course in the near future.

The remaining of this paper is organized as follows. The next section describes the data used and exposes the empirical methodology applied. Section 3 relies on panel data analysis to examine the crisis impact on innovative and young firms. Section 4 presents results on the Juhn-Murphy-Pierce decomposition, and Section 5 summarizes the main results.

2 – Data

For this analysis we combine the World Bank's Enterprise Survey (ES) of 2008 and the three rounds of the World Bank's Financial Crisis Survey (FCS) covering Bulgaria, Hungary, Kazakhstan, Latvia, Lithuania, Romania, and Turkey.

The ES2008 is a comprehensive database of 3,363 firms from manufacturing, retail and other service sectors in those countries, providing information on firm characteristics, various performance measures and the business environment, most of them referred to fiscal year 2007. The ES2008 sample in each country is stratified by firm size, sector and region and is representative of the private non-agricultural formal economy in that year.[4]

The FCS constitutes a panel of longitudinal respondents originally from the ES 2008, interviewed in three rounds: June 2009, January 2010 and June 2010. The participation in FCS was voluntary and the entire original sample of the ES2008 was contacted to determine whether these firms were still in existence or if they had failed and/or became inactive in each FCS wave.

Table 1 shows the number of firms included in the sample of ES2008 (the pre-crisis scenario) for each country, and the firms included in each of the three FCS waves. The dataset contains 3,363 observations for firms in 2008 (the "baseline"); for the following periods the attrition from the panel (due to firm exit and non-responses) is considerable as, on average, 41% of firms are dropped from the original 2008 sample. In order to mitigate this problem and to assure that each FCS wave of the panel is representative of the population in the according period, inverse probability weights were estimated for each wave, in each country, through the adjustment of the ES2008 weights for non-response. With these adjusted weights it is possible to estimate statistics that are representative for the nonagricultural private economy within each country and for each period.

Table 1 – Sampling of ES2008 and FCS

	ES2008 (wave 0)	**FCS-jun 2009 (wave 1)**	**FCS-jan 2010 (wave 2)**	**FCS-jun 2010 (wave 3)**
Turkey	1,152	514	606	364
Romania	541	370	304	303
Kazakhstan	544	-	233	-
Hungary	291	187	152	151
Latvia	271	226	221	206
Lithuania	276	239	224	217
Bulgaria	288	150	152	152
Total Obs.	3,363	1,686	1,892	1,393

Source: Enterprise Survey and Financial Crisis Survey

As we are interested in analyzing the crisis' impact on performance of innovative and young firms, we first classify firms according to their pre-crisis characteristics of age and innovation status.

[4] Detailed information on the Enterprise Surveys can be obtained at http://www.enterprisesurveys.org.

To distinguish the innovative status of the firm, we first define a dummy variable ($Inov_i$) that equals 1 if a firm reports having introduced new products or processes in the period 2005-2007, according to ES 2008 data.[5] As this information is not available in the questionnaire of the FCS waves, we then repeat (for each firm) the value assumed in ES2008 for the following panel periods. As an alternative criterion to classify innovative companies, we defined another dummy variable RD_i that equals one if the firm reports engaging in R&D activities (within the establishment or with other contracted firms) in the 2005-2007 period, also according to ES 2008.[6] As it happens with the $Inov_i$ variable, RD_i is also time invariant.

Table 2 presents the estimated shares of firms that have introduced new product/processes in the 2005-2007 period. It shows, for every country, the proportions of firms in each category differ over time due to the use of weights that adjust for panel attrition. From Table 3, a large share of firms are classified as non-innovative (or as potentially non-innovative) over time – 54% on average for all countries – but there is some heterogeneity across countries, as Latvia and Lithuania have, on average, more innovative than non-innovative firms over time.[7]

Table 2 – Proportions of firms that report having introduced/ not introduced new product or process, by country and panel wave

	ES2008 (wave 0)		FCS Jun 09 (wave 2)		FCS Jan 2010 (wave 3)		FCS Jun 10 (wave 4)	
	No-innovative	innovative	no-innovative	innovative	no-innovative	innovative	no-innovative	innovative
Turkey	56.4%	43.6%	60.0%	40.0%	59.6%	40.4%	64.6%	35.4%
Romania	56.7%	43.3%	51.4%	48.7%	51.6%	48.4%	54.9%	45.1%
Kazakhstan	56.6%	43.4%			46.6%	53.4%		
Hungary	62.2%	37.8%	65.8%	34.2%	60.3%	39.7%	60.7%	39.3%
Latvia	44.7%	55.3%	43.1%	56.9%	47.1%	52.9%	45.1%	54.9%
Lithuania	34.7%	65.3%	33.7%	66.3%	32.4%	67.6%	36.1%	63.9%
Bulgaria	59.9%	40.1%	50.0%	50.0%	58.1%	41.9%	55.0%	45.0%
Total %	55.1%	44.9%	51.5%	48.5%	53.4%	46.6%	55.8%	44.2%
Total Obs Total Obs.	1738	1608	810	868	921	960	668	717

Source: Enterprise Survey and Financial Crisis Survey

[5]The question used in ES 2008 was "In the last three years, has this establishment introduced new products or services?"

[6]The question used in ES 2008 was "In the last three years, has this establishment invested in research and development (in-house or outsourced)?"

[7] Table I in the Annex uses the second criterion to categorize innovative firms and shows the estimated proportions of firms engaged in R&D activities as of 2007, for all waves. It shows that the percentage of firms classified as non-R&D performers (or as potentially non-R&D performers) is large – 77% over time – with no heterogeneity within countries.

To classify firms by age, we define a dummy $Young_i$ for firms up to five years old before the crisis (2007), based on ES2008 data. Table 3 shows the estimated proportions of age groups, by country, for all the four panel periods.

Table 3 – Proportions of young/older companies in 2007, by country

	ES2008 (wave 0)		FCS Jun 09 (wave 1)		FCS Jan 2010 (wave 2)		FCS Jun 10 (wave 3)	
	older	**young**	**older**	**young**	**older**	**young**	**older**	**young**
Turkey	83.4%	16.6%	88.0%	12.0%	88.9%	11.2%	87.6%	12.4%
Romania	76.7%	23.3%	79.0%	21.0%	81.4%	18.6%	82.1%	17.9%
Kazakhstan	59.3%	40.7%			67.6%	32.5%		
Hungary	88.5%	11.5%	89.2%	10.8%	95.0%	5.1%	93.4%	6.7%
Latvia	80.5%	19.5%	82.8%	17.2%	82.0%	18.0%	82.7%	17.3%
Lithuania	76.3%	23.7%	74.9%	25.1%	76.6%	23.4%	79.2%	20.8%
Bulgaria	84.4%	15.6%	88.7%	11.3%	87.4%	12.6%	88.2%	11.8%
Total %	80.0%	20.1%	83.3%	16.7%	84.4%	15.6%	85.5%	14.5%
Total Obs	2666	602	1417	223	1560	288	1170	190

Source: Enterprise Survey and Financial Crisis Survey

Using the innovation and age groups defined above, we focus on a particular dimension of firm's economic performance: sales growth. We calculate sales growth rates in each panel wave. From ES2008 data, we use the sales value declared for fiscal year 2007 and three years prior and compute the annualized growth rate of sales in the 2004-2007 period, i.e the pre-crisis period.[8] For the following waves, based on FCS data, we use the declared sales growth rate for the 12 month period ending in the month of the survey. We then have three 12 month sales growth rates: June 2008 to June 2009, January 2009 to January 2010 and June 2009 to June 2010.[9] Real growth rates were then computed, for each wave, using the GDP deflator from the International Financial Statistics Database.

Due to data availability and assuming the Lehman Brother collapse in September 2008 as the onset of the crisis, we refer to the 2004-2007 period as the pre-crisis period. The following panel periods are then considered to reflect the crisis effects.[10]

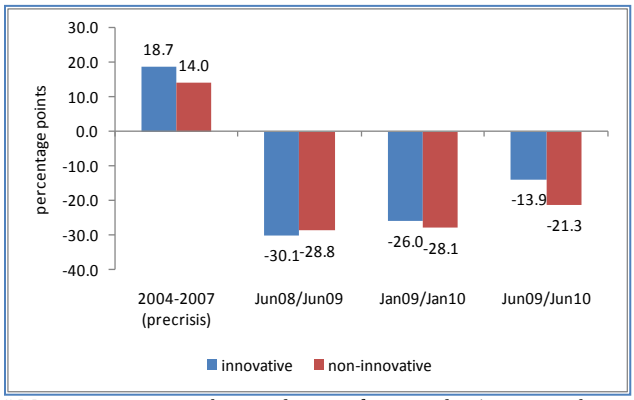
[8] We then controlled for outliers checking the firms for which annualized sales growth rates in the 2004-2007 period were three standard deviations outside the mean growth rate for each country.

[9] As the growth rates for these periods range from -100% to 100%, we didn't control for outliers. We acknowledge that these rates differ from the annualized rate computed for the 2004-2007 period. They were used because there was no other way to measure sales variation in the FCS waves.

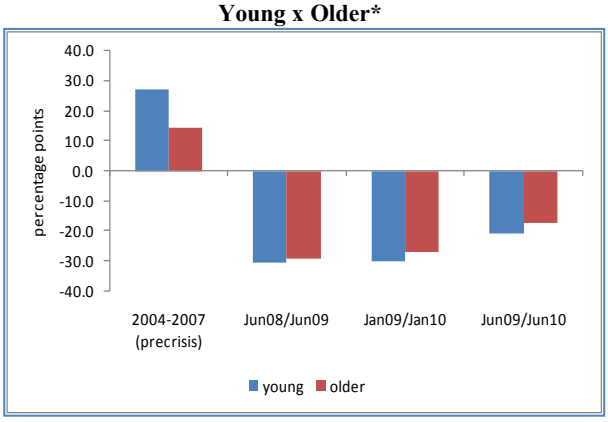
[10] We acknowledge that the first of the FCS waves (measured in June 2009, and with sales growth computed for the June 2008 – June 2009 period) partially overlaps the (real) pre-crisis period as the onset of the crisis (the Lehman Brothers collapse) occurred in September 2008. Therefore, the particular period June 2008 – August 2008 could be

Graph 1 - Averages of Sales Growth Rates (in %)

Innovative x Noninnovative#



Young x Older*



Measuring innovation by introduction of new product/process in the 2004-2007 period

* As in 2007

Source: Source: Enterprise Survey and Financial Crisis Survey

Graph1 shows the average sales growth rate of innovative and non-innovative firms and of young and older firms for the pre-crisis period, computed for 2004-2007 (according to ES2008 data) and the following periods according to FCS waves. [11]

It demonstrates, first, that in the pre-crisis period innovative firms presented higher growth rates than non-innovative companies. In the following intervals, when the effects of the global downturn have showed up, both innovative and non-innovative groups presented negative growth rates. There is however no clear trend of which group presented the largest reduction, and the difference between the growth rates within them has never shown to be statistically significant. The reduction in their sales growth rate was larger than that of their counterparts in FCS wave 1; in waves 2 and 3 this difference had been reversed. Except for the pre-crisis period, none of the differences between the growth rates of the compared groups have shown to be statistically significant. [12,]

Comparing young and older firms, data show that before the crisis young companies grew faster than their counterparts; and this difference was statistically significant at 10% level. In the following waves, however, both groups presented a negative sales growth rate, which always showed to be larger for young firms. None of the differences between these growth rates in the post-crisis periods have shown to be statistically significant.

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capturing the pre-crisis context. However, we assume that this short overlap does not impair the analysis of sales performance of corporate sector.

[11] Graph I the Annex shows the average sales growth rate of innovative and non-innovative firms, according to the second criterion used to classify innovative firms.

[12] In the pre-crisis period, the difference between average of sales growth rate of innovative and non-innovative firms was statistically significant at 5% level.

Overall, these results show that young and innovative companies were growing faster than their counterparts before the crisis. In the following periods, there is no clear trend of which group is the most affected, and none of the comparisons of sales growth rate among the groups proved to be statistically significant.

3 - Panel Data Analysis

The main objective of this paper is to measure the crisis impact on sales growth performance of innovative (young) firms. To the extent that the crisis has impacted the whole economy, our initial identification strategy could rely on the construction of a counterfactual group based on non-innovative (older) firms. However, in practice, such a simple "before and after" comparison between these groups of firms may provide misleading estimates of the crisis impact due to some sort of omitted variables bias that arises from unobserved and/or uncontrolled differences in sales performance between the two groups.

If we assume that the only source of omitted-variables bias comes from observable characteristics, we can then follow Rosenbaun and Rubin (1983) and refine our comparison groups in order to make them similar in terms of every characteristic except for the fact that one is innovative (young) and the other is non-innovative. In other words, if we want to compare innovative (young) and non-innovative (older) firms as a way to assess the impact of the crisis on innovative (young) companies, we need to assure that the comparison of sales performance between the referred groups corrects for possible discrepancies that might exist due to intrinsic differences between them and that might be partially affecting the outcome of interest.

We then begin our estimation strategy using a panel-data analysis, based on Equation 1, in order to assess the difference in sales growth performance between innovative (young) and non-innovative (older) companies, from pre-crisis to the following periods, when controlling for certain observable firm characteristics.[13] The choice of which characteristics to use draws both on the theoretical and the empirical literature, suggesting that attributes such as human capital, size, age, ownership, export orientation and credit access are likely to affect firm evolution (Klette and Kortum (2004), Aw, Roberts and Xu (2008), Seker (2009) and Bernard et al (2007))

From the specification listed in Equation 1, real sales growth rate – represented by g_{it} - is computed for each firm *i* at *t*=4 time periods: 2004/2007, June 2008/June 2009, January

[13] We are not controlling for differences that arise from unobservable characteristics.

2009/January 2010 and July 2009/July 2010. As already defined, $Inov_i$ and $Young_i$ variables control for firm innovative status and firm age in the pre-crisis period, respectively.

$$g_{it} = \beta_0 + \beta_1 t + \beta_2 (t * Inov_i) + \beta_3 (t * young_i) + \theta Z_{it} + u_{it} \quad (1)$$

The time trend variable (t) is categorical and assumes 0 in the pre-crisis period (2004/2007), 1 in June 2008/June 2009, 2 in January 2009/January 2010 and 3 in June 2009/June 2010. Their associated coefficients capture the autonomous sales growth variation that is common to all firms in each of the periods following the crisis. The coefficients on time interactions with $Inov_i$ and $Young_i$ variables reflect the crisis impact on sales growth performance of innovative and young firms, respectively, in each of the periods following the crisis. Z_{it} is a vector of control variables To control for firm-size we include the dummies $Small_{it}$ (11-50 full time employees), $Medium_{it}$ (51-250) and $Large_{it}$ (≥251); these size groups are determined according to firm employment level in each of the four panel periods, and the omitted category is $Micro_{it}$. To test if globally engaged firms – exporting or foreign ownership – grow faster than non-exporters and domestically owned firms, we include dummies for export orientation and ownership. $Export_{it}$ distinguishes firms that generate more than 10% of their sales from exports; it is determined according to information for each of the four panel periods. To assess how credit dependence affects firm performance, we include the variable $WK.int_{it}$ which measures the percentage of firm's working capital that is financed from internal funds in each of the four panel periods. $Foreign_i$ controls for firms with 10% or more of foreign ownership; this variable is available only for 2007, through the ES2008 data, and so we repeat the value assumed in t=1 for the following periods t=2, t=3 and t=4. As a way to control for the skill intensity of the firm we include a dummy $Skill_i$ defined as more than 20% of employees with university. This information is only available for 2007, through the ES2008 data, and so the value assumed in t=1 is repeated for the following periods t=2, t=3 and t=4.[14] $Sector_i$ and $Country_i$ control for the 2-digit industry and the country of the firm; the omitted categories are "other manufacturing" sector and Bulgaria, respectively. The error term u_{it} is defined as:

[14] Therefore, the variable $Skill_i$ is also time-invariant, and reflects, in the t=2, t=3 and t=4 periods, the potentially skilled intensive firms.

$$u_{it} = \alpha_i + \varepsilon_{it} \qquad (2)$$

Following a fixed effect model, the time invariant component of the error (α_i) is possibly correlated with regressors, while the idiosyncratic error is uncorrelated with the regressors. We use two different estimators: the within estimator and the Hausman-Taylor (HT) estimator.

The within estimator provides consistent estimation; however, since it uses only within variance for the estimations and disregards the between variance, it does not obtain estimations for time invariant variables, as $Skill_i$, $Foreign_i$, country and industry controls, and also for $Inov_i$ and $Young_i$. This is particularly disadvantageous, as the $Inov_i$ and $Young_i$ coefficients could give us useful information on the measurement of average difference of sales growth rate of innovative and young firms compared to their respective counterparts at the baseline (the pre-crisis period). This approximates possible differences of sales growth performance between the referred groups in the absence of a crisis.

On the other hand, the HT estimator enables the consistent estimation of all the time invariant variables. At the same time, and more importantly, the HT estimator controls for limited form of endogeneity that is present in a fixed effect model, which is certainly the case of the $Inov_i$ variable, as firms with high unobservable ability are likely to be innovative and have better sales performance.[15] Therefore, when applying this estimator we are not controlling only for the observable but also for the unobservables factors that might be correlated and can potentially bias the estimation of the crisis impact on sales performance of innovative firms. [16]

After running a Hausman test that confirmed the fixed effect specification for Eq. (1)[17], we first apply the within estimator with clustered standard errors to allow for possible

[15] In brief, the HT procedure estimates a random effect model through an instrumental variable technique that uses only information contained in the model to eliminate the correlation between the error term and the included variables (which leads to the rejection of the random-effects model). More specifically, the HT procedure uses exogenous time-invariant variables plus the unit means of the exogenous-varying variables as instruments for the endogenous time-invariant variables. As a result, the HT technique allows the estimation of time-invariant variables without compromising the estimates for time-varying variables.

[16] We assumed that the exogenous variables $Skill_i$, $Foreign_i$, $Young_i$, $WK.int_{it}$, country and industry controls were instruments for the endogenous, time-invariant, variable $Inov_i$ and also for the endogenous time-variant variable $Export_i$. The correlation analysis between these variables showed that all the instruments were sufficiently correlated to identify the coefficient on $Inov_i$.

[17] The Hausman test presented evidence in favor of the fixed effect model. The overall statistic of the Hausman test (which assumed the null hypothesis that the random effect estimator was fully efficient) was rejected, both for the model with t=4 (Prob>Chi2= 0.0776) as for the t=3 (Prob>Chi2= 0.0451).

correlations in growth rates across firms within the same country and industry. Table 4 displays the results for both estimators.

Table 4 - Explaining sales growth rate over time: a panel data analysis#
(robust standard errors in parenthesis)

	Innovation measured as introduction of product/process		**Innovation measured by the performance of R&D**	
	within estimator (1)	**Hausman-Taylor estimator (2)**	**within estimator (3)**	**Hausman-Taylor estimator (4)**
June 08/June 09 (time2)	-37.738***	-37.939***	-41.024***	-41.925***
	(5.675)	(0.332)	(4.225)	(0.259)
Jan 09/Jan 10 (time3)	-38.147***	-39.292***	-39.084***	-40.006***
	(6.022)	(0.342)	(5.924)	(0.272)
June 09/June10 (time 4)	-27.095***	-29.283***	-27.919***	-29.087***
	(6.639)	(0.353)	(6.508)	(0.277)
Inov	.	13.150***	.	20.368***
	.	(0.368)	.	(0.458)
time2XInov	-13.022	-14.371***	-19.517	-19.208***
	(7.919)	(0.449)	(12.320)	(0.557)
time3XInov	-7.699	-9.300***	-16.079	-20.844***
	(9.543)	(0.457)	(13.642)	(0.554)
time4XInov	-9.301	-8.931***	-20.579	-23.206***
	(10.331)	(0.474)	(13.002)	(0.577)
Young	.	32.701***	.	31.333***
	.	(0.479)	.	(0.472)
time2XYoung	-38.439*	-31.321***	-36.751	-29.423***
	(22.726)	(0.649)	(22.315)	(0.639)
time3XYoung	-49.078**	-36.068***	-47.826**	-35.010***
	(22.462)	(0.698)	(22.305)	(0.686)
time4XYoung	-44.973**	-35.131***	-44.960**	-35.285***
	(21.999)	(0.694)	(21.675)	(0.681)
skill	.	2.804***	.	2.980***
	.	(0.255)	.	(0.253)
foreign	.	5.258***	.	5.660***
	.	(0.380)	.	(0.380)
small	7.275	8.245***	7.707	8.936***
	(9.549)	(0.223)	(9.816)	(0.220)
medium	9.684	15.621***	8.031	15.839***
	(10.856)	(0.358)	(11.271)	(0.354)
large	11.816	19.886***	9.895	19.644***
	(14.860)	(0.712)	(15.555)	(0.708)
Export	-6.686	-6.245***	-6.366	-5.931***

	(6.230)	(0.452)	(5.755)	(0.449)
WK.int	0.046	0.051***	0.047	0.046***
	(0.079)	(0.002)	(0.076)	(0.002)
Country controls	Yes	Yes	Yes	Yes
Sector controls	Yes	Yes	Yes	Yes
_cons	11.527	-13.428***	11.781	-11.594***
	(10.528)	(0.578)	(10.580)	(0.559)
N.obs	2527	2527	2530	2530
F/Chi2	18.16	88320.07	17.84	90996.47
Prob>F/Prob>Chi 2	0.00	0.00	0.00	0.00

*** p<0.01, ** p<0.05, * p<0.1

Table II in the Annex presents the complete results, including the sector and country controls

We find that the common impact of the crisis on all firms – captured by the coefficients on time trend - was decreasingly negative (though not in a monotonic way) and statistically significant. For instance, in column (1), the within estimator showed that the crisis lead to a reduction of 37.78 percentage points in the June 2008/June 2009 period. In the following period (January 2009/January 2010) the impact was still negative, but larger in magnitude, 38.15 percentage points, and in the last period (June 2009/June 2010), the estimated impact was a reduction of 27.09 percentage points.

The estimated coefficients on time interaction, in columns (1) and (2), show that when controlling for firm-specific characteristics, innovative firms have always presented larger reductions in sales growth when compared to non-innovative firms, and the difference in sales drop within these groups of firms has decreased overtime. While the within estimator results - column (1) - didn't show to be statistically significant, the HT estimator pointed to similar results but with better inference (see column (2)). In June 2008/June 2009 period, the sales growth rate of innovative companies reduced by 14.37 percentage points more than non-innovative companies. For the following period (January 2009/January 2010), the innovative group continued to be more affected: the decline in its sales growth has been 9.3 percentage points larger than for the non-innovative group. Finally, in the period July 2009/July 2010, innovative firms continued to be more affected: a sales drop 8.9 percentage points higher than the comparison group. All of these $t * Inov_i$ coefficients showed to be statistically significant at the 1% level.

The HT result also show, through the estimation of the $Inov_i$'s coefficient, that the *average* sales growth rate of innovative firms was higher than the average for non-innovative

group before the crisis. Therefore, the fact that the crisis impact on sales performance of innovative firms has shown to be negative, though in a declining pace, suggests that, as time goes by, the crisis might be eroding the competitive advantage that innovative companies had before the crisis, with possible consequences for a recovery process.

To check whether possible correlations between innovation and export orientation variables could influence these results, we measured the impact of the crisis on innovative firms that are also export oriented.[18] Table III in the Annex reports the complete set of results of the HT estimator. The results showed that innovative firms who are export oriented were positively impacted by the crisis, having grown more than the other firms. Two possible explanations to this result are: first, that innovative and export-oriented firms were able to better diversify market-risk (and thus were less affected by demand fluctuations in one single country), and second, that those firms supply goods with higher "intrinsic value" (and so have higher monopoly power despite operating in an international market).

We also checked whether the results of a negative impact on innovative firms are robust to the way innovative firms are classified. We re-estimate the sales growth equation (Eq.(1)) using the development of R&D activities in the 2004-2007 period as an alternative criterion to categorize innovative firms (see columns (3) and (4)). Both the within estimator and the HT pointed to a larger sales reduction of companies with R&D activities in all periods (when compared to companies without R&D efforts). The difference in sales drop between these two firms' groups was shown to be increasing overtime. The HT estimator also revealed that the average sales growth rate of firms with R&D activities was superior to the average of non R&D performers before the crisis, which leads to the same conclusion that the competitive advantage that R&D performers had prior to the crisis might be eroding overtime.

With regard to young companies, the results reported in Table 4 for both estimators show that the crisis impact has been increasingly more severe for young firms. The results of HT estimator (column (2)) points that the decline in sales growth of young firms was 31.32 percentage points higher than the reduction experienced by the older firms in the period June 2008/June 2009 In the following two periods, the difference in sales decline between the two compared groups was even larger: 36.06 percentage points (in January 2009/January 2010) and 35.13 percentage points (in June 2009/June2010). All of these estimations were statistically

[18] We included a time interaction with a categorical variable $Inov\_Export_{it}$, which distinguishes innovative status and export orientation across firms.

significant. From the result of the $Young_i$ coefficient, we found that before the crisis, the average sales growth rate of young companies was higher than the average rate of older firms. As was the case when comparing innovative vs. non-innovative firms, a positive sign for the $Young_i$ variable combined with negative signs for $t * Young_i^{'}$'s coefficients suggest that the competitive advantage that young firms had before the crisis might be eroding over time.

The findings in Table 4 also show other interesting patterns. First, skills intensive firms presented, on average, (significantly) higher sales growth than non-skills intensive firms; a positive difference that varies from 2.8 to 2.98 percentage points. Second, foreign owned firms presented a significantly higher average growth rate than their counterparts; a positive difference varying from 5.25 to 5.66 percentage points. Third, relative to micro firms, small, medium and large companies had significantly higher average sales growth rates. Fourth, results show a slightly (though significantly) positive association between the proportion of working capital financed from internal funds and sales growth, which means that firms that rely more on internal finance (and thus less on external finance) grew, on average, slightly more over the crisis period. This result seems consistent with the findings of Kannan (2010) who reported that industries that rely more on external finance grow more slowly during financial crisis.

Finally, to examine whether the inclusion of data from FCS wave 2 - collected in January 2010 - could bias the results, due to possible seasonal effects (as the other post-crisis periods were both measured at the same month of the year, June), we conduct robustness checks excluding this data. Our inferences were unaffected by this sample restriction (see Table IV in the Annex). The impact continued to be measured as negative for innovative firms,[19] and increasingly negative for young firms. Both of the results were statistically significant.

The estimation analysis made so far relied on the use of a regression model where we control for firm heterogeneity between innovative (young) and non-innovative (older) firms in order to estimate the impact of the crisis on innovative (young) firms. One could argue that we might not have used the best way to control for firm heterogeneity between the compared groups, and specifically, that the inclusion of covariates in the model does not address the fact that the groups being compared may have distinct distribution of control variables, and this lack of distributional overlap might yield an ineffective comparison set.

[19] The speed of this negative impact depends on the way we classify innovative firms. When innovative firms are classified by the introduction of a new product/process, the impact was decreasingly negative. When using the other criteria to classify innovative firms (R&D activities), the impact is increasingly negative.

In order to overcome this issue, we use the propensity score matching (PSM) method as an alternative way to adjust for pre-crisis observable differences between innovative and non-innovative (and between young and older) firms. Basically, the idea behind this method is that of taking innovative (young) firms before the crisis, and then, from the sample of non-innovative (older), identify comparison firms that best match the innovative (young) firms in terms of covariates already chosen (size, export orientation, use of skilled workforce, foreign ownership, country and sector) and pre-crisis sales level. Based on this framework, the set of counterfactuals is then restricted to the matched comparison firms, and once these matched firms are selected in the baseline (in the pre-crisis period), we then run the HT estimator - which, as already discussed also controls for unobservables - to assess the impact of the crisis on innovative and young companies.

Table 5 reports the results of HT estimations on crisis impact on innovative firms based on the previous use of PSM. For quick reference, the table also reports the results of HT estimations without PSM – as shown in Table 4.

Table 5 – Estimated crisis impact on sales growth performance of innovative companies: results for Hausman Taylor estimator with and without PSM

(robust standard errors in parenthesis)

	Innovation measured as introduction of product/process		**Innovation measured by the performance of R&D**	
	HT with PSM	**HT without PSM**	**HT with PSM**	**HT without PSM**
time2XInov	-16.502***	-14.371***	-11.550***	-19.208***
	(0.467)	(0.449)	(0.557)	(0.557)
time3XInov	-9.032***	-9.300***	-3.689***	-20.844***
	(0.521)	(0.457)	(0.608)	(0.554)
time4XInov	-8.842***	-8.931***	-28.188***	-23.206***
	(0.534)	(0.474)	(0.637)	(0.577)
N.obs	1510	2527	1505	2530

*** p<0.01, ** p<0.05, * p<0.1

Overall, the "HT with PSM" results continued to point to the same picture as before: the differential impact of the crisis was significantly larger for innovative firms. Again, how much more vulnerable the innovative firms were to the slowdown depend on the variable used to measure innovation. If measuring innovation by the introduction of a product/process, the difference in sales drop within innovative and no-innovative firms decreases overtime; when classifying innovative firms by their R&D activities, the difference increases.

Table 6 presents the estimated impacts of the crisis on sales performance of young companies based on HT estimator with previous use of PSM. The new estimations also pointed to larger negative impacts on young firms when compared to older companies, but at this time the difference in sales drop within young and older firms was considerably smaller than previously reported. Despite these differences in magnitude, the new estimations continued to point to the same picture as before, that young firms were significantly more affected by the crisis, and that the difference in sales drop within the compared groups of firms increased (though not monotonically) over time.

Table 6 – Estimated crisis impact on sales growth performance of young companies: results for Hausman Taylor estimator with and without PSM

(robust standard errors in parenthesis)

	Innovation measured as introduction of product/process		**Innovation measured by the performance of R&D**	
	HT with PSM	**HT without PSM**	**HT with PSM**	**HT without PSM**
time2XYoung	-3.767***	-31.321***	-1.187	-29.423***
	(1.265)	(0.649)	(1.229)	(0.639)
time3XYoung	-14.821***	-36.068***	-11.222***	-35.010***
	(1.506)	(0.698)	(1.500)	(0.686)
time4XYoung	-6.123***	-35.131***	-8.234***	-35.285***
	(1.521)	(0.694)	(1.477)	(0.681)
N.obs	346	2527	346	2530

*** p<0.01, ** p<0.05, * p<0.1

4 - Juhn-Murphy-Pierce Decomposition

When assessing the differential impact of the crisis on sales growth performance of innovative firms (vs. non-innovative), the results so far showed that innovative companies have been significantly more affected. For young firms, the evidence pointed that young firms have suffered more with the crisis, when compared to older companies. In this section we try to explain the difference between sales growth rates of innovative and non-innovative firms as well as between young and older firms. To do that, we use the Juhn-Murphy-Pierce (JMP) decomposition. This technique was first employed by Juhn, Murphy and Pierce (1993) and applies micro-simulation techniques to decompose the differences between two outcomes distributions for two population sub-groups.[20]

[20] This method is a variant of the classical Oaxaca and Blinder decomposition technique, widely applied in labor economics to explain wage differentials between groups of workers (Oaxaca, 1973 and Blinder,1973) When compared to the Oaxaca-Blinder method, the JMP decomposition technique has the distinct advantage of dealing

Following Juhn, Murphy, and Pierce (1993) the framework is then defined. First, after estimating an OLS model to explain the sales growth rate of two population sub-groups separately (for instance, innovative and non-innovative companies), we define two models:

$$y_1 = x_1\beta_1 + u_1 \quad (3)$$

$$y_2 = x_2\beta_2 + u_2 \quad (4)$$

where 1 and 2 set the innovative and non-innovative groups of firms.

y_1 and y_2 are the vectors of the values of the dependent variable - sales growth rate - in the two firm groups.

x_1 and x_2 are the data matrices (observable characteristics) for the two firm groups. As we did in the panel data analysis, we follow the literature to choose those observable characteristics that are reasonable predictors to explain firm performance. Therefore, when comparing innovative and non-innovative companies, we select: dummies for current size of firms, a dummy for use of skilled labor in the pre-crisis period, a dummy for current export orientation, a dummy for firm ownership in the pre-crisis period, share of working capital financed from internal funds, country and sector controls. [21]

β_1 and β_2 are the vectors of estimated coefficients (observable returns – "market values" of those characteristics) for the two sub-groups; and u_1 and u_2 are the vectors of estimated residuals (unobservable, i.e., unmeasured characteristics and returns) for the same sub-groups.

Let $F_1(.)$ and $F_2(.)$ denote the cumulative distribution functions of the residuals for innovative and non-innovative groups, respectively. Therefore, if we take

$$p_{i1} = F_1(u_{i1}|x_{i1}) \quad (5)$$

explicitly with the residuals from the estimation, therefore considering three components (characteristics, return and unexplained effects), while Oaxaca-Blinder deals with only two (characteristics and return effects).

[21] For the comparison young and older firms, the set of characteristics includes: size in the period, innovation status in the pre-crisis period, use of skilled labor in the pre-crisis period, export orientation in the period, ownership in the pre-crisis period, country and sector fixed effects.

to be the percentile of an individual firm's (i) residual in the residual distribution of innovative firms, we can write:

$$u_{i1} = F_1^{-1}(p_{i1}|x_{i1}) \qquad (6)$$

where $F_1^{-1}(.)$ is the inverse of the cumulative distribution function for the "innovative firms" group. The same procedure can be done to write the individual residual in the residual distribution of non-innovative companies.

Next, assume $\overline{F(.)}$ to be the reference residual distribution (e.g., the average residual distribution over both samples) and let $\bar{\beta}$ be an estimate of benchmark coefficients (e.g, the coefficients from a pooled model over the two firm groups). Based on this framework we can construct hypothetical outcome distributions with any of the three components held fixed. We can then determine:

(A) hypothetical outcomes with varying observable characteristics but with fixed coefficients and fixed residual distribution as

$$y_{i1}^{(A)} = x_{i1}\bar{\beta} + \overline{F^{-1}}(p_{i1}|x_{i1}) \qquad (7)$$

$$y_{i2}^{(A)} = x_{i2}\bar{\beta} + \overline{F^{-1}}(p_{i2}|x_{i2}) \qquad (8)$$

(B) hypothetical outcomes with varying observable characteristics and varying coefficients but with a fixed residual distribution as

$$y_{i1}^{(B)} = x_{i1}\beta_1 + \overline{F^{-1}}(p_{i1}|x_{i1}) \qquad (9)$$

$$y_{i2}^{(B)} = x_{i2}\beta_2 + \overline{F^{-1}}(p_{i2}|x_{i2}) \qquad (10)$$

(C) hypothetical outcomes with varying observable characteristics, varying coefficients and varying residual distribution as

$$y_{i1}^{(C)} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \quad (11)$$

$$y_{i1}^{(C)} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \quad (12)$$

These last outcomes are actually equal to the originally observable values:

$$y_{i1}^{(C)} = y_{i1} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \quad (13)$$

$$y_{i2}^{(C)} = y_{i2} = x_{i2}\beta_2 + F_2^{-1}(p_{i2}|x_{i2}) \quad (14)$$

Let a capital letter stand for a summary statistic of the distribution of the variable denoted by the corresponding lower-case letter. For instance, Y may be the mean of the distribution of *y*. So, the differential $Y_1 - Y_2$ can be decomposed as:

$$Y_1 - Y_2 = \left[Y_1^{(A)} - Y_2^{(A)}\right] + \left[\left(Y_1^{(B)} - Y_2^{(B)}\right) - \left(Y_1^{(A)} - Y_2^{(A)}\right)\right] + \left[\left(Y_1^{(C)} - Y_2^{(C)}\right) - \left(Y_1^{(B)} - Y_2^{(B)}\right)\right] \quad (15)$$

$$= T = C + R + U$$

where T is the total difference; C can be attributed to differences in observable characteristics - the characteristics (or quantity) effect; R to differences in observable returns – the return (or price) effect, and U to differences in unobservable quantities and returns – the unexplained (or residual) effect.

In this paper, as we are using the JMP method to analyze the difference of sales growth performance distribution between the two groups of firms, the first component – characteristics (or quantity) effect – captures the part of the difference of sales growth performance between the referred groups that is due to differences in observable characteristics (quantities). In other words, it quantifies to what extent innovative (young) firms have a more favorable "endowment" in terms of observable characteristics as compared to non-innovative (older) companies. For

example, one firm category might have firms with, on average, larger sizes, larger use of skilled workforce, larger export orientation, and these might lead to higher growth sales performance.

The second component, the return (or price) effect, reflects the part of the gap of sales growth performance between the two groups of firms that is due to differences in returns of those observable characteristics. In other words, it measures to what extent the returns of those observable characteristics on the sales performance of a firm differ between innovative (young) and non-innovative (older) companies. For example, one firm category might get larger returns from the same observable characteristics when compared to other firm group.

The third component, the unexplained (or residual) effect, captures the unmeasured factors that affect the performance of the two groups. In other words, it measures the part of the difference of the sales growth performance between the two groups of firms that is due to either difference in unobservable characteristics and returns or to a measurement error. Assuming that the OLS models which explain sales performance of the two companies' cohorts are satisfactorily specified, any unmeasured factors that affect the performance of these two groups will be captured by this residual effect. For the comparison between innovative and non-innovative firms, we interpret this residual effect as a proxy of the difference between the two firm cohorts in terms of some intangible assets, such as the specialized knowledge embodied in researchers, the firms' entrepreneurship ability, or its "animal spirits." Taking the innovative group as the reference, this effect could be interpreted as the *innovation premium*. When comparing young and older firms, this residual effect captures the differences between the two groups in terms of the firms' intangible assets related to age, such as the ability to appropriate of learning benefits. If we assume the young firms as the reference group, this residual effect could be interpreted as *the ability to learn of young firms*.

We apply the JMP technique using data of each one of the periods: pre-crisis (2004-2007), June 2008/June 2009, January 2009/January 2010, and June 2009/June 2010. Table 8 presents the results for the sample means of the distribution of sales growth difference between innovative/non-innovative in each one of the periods. The complete results for all the main percentiles of these distributions are in Table V in the Annex.[22]

[22] As the employment of JMP technique relies on the use of separate OLS regressions to explain the sale performance of each group of firms, we apply OLS estimators with robust standard errors when considering the data for each period. The OLS estimations in each period apply the accordingly weights: for the pre-crisis period, we used the cross-sectional weights of ES2008, and for the following periods we used the weights of each FCS round.

As the aim of the analysis is to explain the sales growth performance of innovative companies relative to non-innovative firms, the distinct components that explain the sales performance gap between these firm groups (characteristics, return and unexplained effects) are considered from the point of view of innovative companies.

Table 7 - Decomposing the total difference of sales growth rate between innovative and non-innovative firms: JMP results for the mean of the distribution

Period	Total Difference	Characteristics Effect	Return Effect	Residual Effect
Pre-crisis period (2004-2007)	12.79	-2.97	15.51	0.26
	100%	*-23.3%*	*121.2%*	*2.0%*
June 08 – June 09	-0.87	-0.28	-0.73	0.15
	100%	*32.6%*	*84.1%*	*-16.8%*
January 09-January 10	3.73	5.30	-1.48	-0.08
	100%	*142.0%*	*-39.8%*	*-2.2%*
June 09- June10	8.21	3.40	5.13	-0.32
	100%	*41.5%*	*62.5%*	*-3.9%*

For the pre-crisis period, Table 7 shows that the total difference between sales growth performance of innovative and non-innovative companies amounts to 12.79 percentage points (in favor of innovative). This positive gap was mainly due to the return effect, revealing that the returns of the observable characteristics were higher for innovative companies, even though the characteristic effect was not favorable for the innovative group. The residual effect showed to be also positive, suggesting that, before the crisis, unobservable factors favor the innovative companies. We interpret this as an indication of the existence of a positive premium for the entrepreneurship ability, or the "animal spirits," of innovative companies before the onset of the crisis.

For the following periods, the total difference was initially negative for innovative firms – pointing towards a drastic change in the pattern of comparative sales performance of the two groups of firms, when comparing to the pre-crisis period – but returned to be positive afterwards – which seems to indicate a recovery in the relative performance of the innovative group.[23]

[23] As Graph 1 has indicated, both innovative and non-innovative firms have shown negative sales growth rates in all of the periods from June 2008. Therefore, the fact that the JMP results have pointed to an increasingly positive difference between those rates means that, when controlling for observable covariates (through an OLS model), the innovative group presented a less negative sales growth performance in the referred periods. This is consistent with the assessment of the crisis impact through panel data estimators, as they have shown that, in the same time frames, innovative companies have been negatively affected, though in a decreasing rate.

The return effect followed a similar path in the periods following the onset of the crisis: initially negative but ending up as positive in the June 2009/June 2010 period. These results indicate that the returns obtained from innovative firms were initially smaller but turned to be higher from June 2009. The characteristics effect also seemed to receover overtime. On the other hand, the residual effect has shown a clearly weakening course in the same periods under analysis, which suggests that differences in unobservables turned to be increasingly negative against the innovative firms overtime.

Overall, the JMP results suggest that innovative firms might be recovering – as the return and the characteristic effects have shown to be improving since the crisis. However, considering that unmeasured factors have on average been (increasingly) unfavorable to innovative companies, this can be seen as evidence of a negative premium for innovation efforts which might hamper the growth prospects of innovative firms.

Table 8 presents the JMP decomposition technique to examine the gap of sales growth performance between young and older companies in each period. Only the results for the mean of the distributions are presented. The complete results for all the main percentiles of these distributions are in Table VI in the Annex.[24] As the aim of the exercise is to explain the sales growth performance of young companies relative to older firms, the three effects that explain the sales performance gap between the two groups are considered from the point of view of young companies.

[24] See Note 20

Table 8 - Decomposing the total difference of sales growth rate between young and older firms: JMP results for the mean of the distribution

Period	Total Difference	Characteristics Effect	Return Effect	Residual Effect
Pre-crisis period (2004-2007)	28.35	8.16	24.15	-3.95
	100%	*28.8%*	*85.2%*	*-13.9%*
June 08 – June 09	0.26	2.27	0.17	-2.18
	100%	*876.8%*	*66.6%*	*-843.4%*
January 09-January 10	-5.42	-0.88	-2.76	-1.78
	100%	*16.2%*	*50.9%*	*32.9%*
June 09- June10	-6.79	-8.03	4.29	-3.05
	100%	*118.3%*	*-63.1%*	*44.9%*

For the pre-crisis period, Table 8 shows that, on average, the total difference between sales growth performance of young and older companies was 28.35 percentage points (in favor of young firms). The returns of the observable characteristics were higher for younger companies and this accounts for the largest part of that positive difference. The residual effect was negative, which we interpret as evidence that the ability of young firms to benefit from the learning process was inferior to the ability of older companies even before the crisis.

For the following periods, the results show an increasingly negative gap between the sales growth performance of young and older companies, indicating a reversal of the comparative sales performance of the two groups of firms. While the characteristics effect has shown to be decreasing since the crisis, the return effect has shown to be positive in most periods of time, suggesting that the returns obtained by young firms have been higher overtime. However, this was not enough to reverse the worse performance of young firms. The residual effect continued to be negative; which means that the ability of young firms to capture the learning benefits was persistently negative, and this contributed to explain the worse performance of young firms since the crisis.

Overall, the JMP results suggest that young firms are performing even worse since the crisis. Besides, the residual effect was never positive for young companies, possibly indicating that the ability of young firms to benefit from the learning process was always inferior to the ability of older companies, and that this ability has not played a relevant role in young's firm survival.

5 - Conclusions

Following Correa and Iootty (2010), we continued to examine how the sales performance of innovative and young firms has evolved since the global downturn, in order to understand the growth prospects of Eastern European countries. We used a unique panel data for 3,363 firms in seven countries (Bulgaria, Hungary, Kazakhstan, Latvia, Lithuania, Romania, and Turkey) covering manufacturing, retail and other service sectors. Two empirical methods were used. First, we applied a panel-data analysis with fixed effects, with different estimators, in order to assess the impact of the crisis on sales growth performance of innovative and young firms, when controlling for certain firm characteristics. Second, we used the Juhn-Murphy-Pierce technique to decompose – in each of the periods – the difference in sales growth performance between innovative (young) and non-innovative (older) companies into three effects: characteristics effect; returns effect and unexplained effect.

The panel data analysis showed, *first*, that the common impact of the crisis on sales growth performance of all firms was significantly negative, though in a decreasing rate, regardless the estimator applied (within estimator or HT estimator). For instance, in the June 2008/June 2009 period, the within-estimator pointed to a reduction of 37.78 percentage points, while in the June 2009-June 2010 period, the estimated impact (with the same estimation method) was a reduction of 27.09 percentage points.

Second, when then examining how innovative have been particularly affected, panel data analysis showed that the decline in sales growth of innovative firms was always (significantly) larger than the sales reduction experienced by non-innovative firms. This result was robust to the estimator applied (Hausman-Taylor with and without propensity score matching). How innovative firms were more (negatively) affected than no-innovative firms depends, however, on the criteria used to categorize innovation. If measuring innovation by the introduction of a product/process, the difference in sales growth reduction between the two groups of firms decreased over the period. When distinguishing innovative firms by R&D performance, the difference in drop of sales growth between innovative and no-innovative was increasing. It is worth to highlight however that innovative firms who are export oriented were positively impacted by the crisis, having grown more than the other firms.

Third, the panel data estimators also showed that the sales growth performance of young firms was (significantly) more affected than older firms, a result that was robust to the estimator used (within estimator, Hausman Taylor and Hausman-Taylor with propensity score matching).

The estimated difference in sales growth reduction between young and old firms increased overtime.

Going back to the comparative sales performance of innovative (vs. no-innovative) and young (vs. older) groups of firms, the JMP results showed that innovative firms performance might be improving as the return and the characteristic effects have shown to be recovering since the crisis. However, the fact that, on average, unmeasured factors have been (increasingly) unfavorable to innovative companies can be seen as evidence of a negative premium for innovation, which might hamper the growth prospects of innovative firms.

Second, for the young vs. older comparison, the JMP results suggest that young firms are performing even worse since the crisis. The fact that the residual effect has never shown to be positive for young companies, possibly indicating that the ability of young firms to benefit from the learning process was always inferior to the ability of older companies, might reinforce the negative growth course for young firms in the near future.

Overall, our results seem to provide robust evidence that the crisis has negatively affected sales performance of innovative and young companies in Eastern Europe. We do acknowledge that our assessment of the crisis impact was focused on one specific real variable: sales. We did not focus, for instance, on crisis consequences on debt or employment levels, and so we did not check if job losses were larger for innovative firms which could lead to depreciation of human capital. However, sales decline is a reasonable proxy to illustrate the possible crisis consequences on growth prospects. For instance, lower sales might be leading financially constrained, innovative firms to hold back their R&D spending, which could precipitate their decline. The fact that the premium of the ability to innovate has been diminishing suggests that the market is undervaluing their innovative efforts, which could lead to the premature exit of some of these innovative firms. Similarly, the declining sales brought by the crisis might be punishing potentially viable young firms, and the fact that these firms' ability to appropriate from learning benefits is getting even smaller compared to that of older firms might indicate that their ability to contribute to productivity growth is being reduced.

References

Aw, Bee Y., Mark J. Roberts and Daniel Y. Xu (2008), "R&D Investments, Exporting and the Evolution of Firm Productivity," American Economic Review, Papers and Proceedings, 98:2, pp. 451-456.

Bernard, A.B, J. Branford Jensen, S.J Redding, and Schott, P.K. (2007), "Firms in International Trade", Journal of Economic Perspectives, 21(3), pp.105-30.

Blinder, Alan S. (1973). "Wage Discrimination: Reduced Form and Structural Variables." Journal of Human Resources, 8: 436-455

Correa, Paulo and Mariana Iootty. (2010) "Will the Crisis Affect the Economic Recovery in Eastern European Countries: evidence from firm-level data" World Bank Policy Research Working Paper n. 5278

Dunne, Timothy, Roberts, Mark. J, and Larry, Samuelson, (1989). "The Growth and Failure of U.S. Manufacturing Plants," The Quarterly Journal of Economics, MIT Press, vol. 104(4): 671-98

Field, Alexander (2009) "The Great Depression, the New Deal, and the Current Crisis" Challenge, Vol. 52, July-August

Geroski, P.A., 2005. Understanding the implications of empirical work on corporate growth rates. Managerial and Decision Economics 26:129–138.

Gorton, G., 2008. "The Panic of 2007". NBER Working Paper n. 14358

IMF (2009), World Economic Outlook.

Juhn, Chinhui, Kevin M. Murphy, Brooks Pierce (1993). "Wage Inequality and the Rise in Returns to Skill". Journal of Political Economy 101(3): 410-442

Klepper, S., & Thompson, P. (2007). Submarkets and the evolution of market structure. RAND Journal of Economics 34(4): 862-888

Oaxaca, Ronald (1973). "Male-Female Wage Differentials in Urban Labor Markets," International Economic Review, 14 (October): 693-709

Kannan, P. (2010), ""Credit Conditions and Recoveries from Recessions Associated with Financial Crises," IMF Working Papers 10/83

Reinhart, C.M and Rogoff, K.S. (2008), "is the 2007 Sub-prime Financial Crisis So Different? An International Historical Comparison, " American Economic Review. 98(2), 339-344.

Romer, C (2009) "Lessons from the Great depression for Economic recovery in 2009" presented at the Brookings Institution, Washington DC, March 2009.

Rosenbaum, P. and Rubin, D. B. (1983), 'The Central Role of the Propensity Score in Observational Studies for Causal Effects', Biometrika, 70, 41-55.

Schumpeter, J (1942) Capitalism, Socialism and Democracy. New York: Harper.

Seker, Murat (2009). "Importing, Exporting and Innovation in Developing Countries", World Bank Policy Research Working Paper n.º 5156.

World Bank (2008). Unleashing Prosperity: Productivity Growth in Eastern Europe and the Former Soviet Union.

World Bank, (2010). Global Economic Prospects: Crisis, Finance and Growth

Annex

Table I– Proportions of firms that report being engaged/not engaged in R&D activities, by country and panel wave

	ES2008 (wave 0)		FCS Jun 09 (wave 1)		FCS Jan 2010 (wave 2)		FCS Jun 10 (wave 3)	
	non-innovative	innovative	non-innovative	innovative	non-innovative	innovative	non-innovative	innovative
Turkey	77.3%	22.8%	70.5%	29.5%	78.6%	21.4%	77.5%	22.5%
Romania	80.9%	19.1%	77.1%	22.9%	76.3%	23.7%	78.9%	21.1%
Kazakhstan	90.0%	10.0%			90.6%	9.4%		
Hungary	88.6%	11.4%	90.3%	9.7%	92.1%	7.9%	90.0%	10.0%
Latvia	84.8%	15.2%	84.4%	15.7%	82.5%	17.5%	83.6%	16.4%
Lithuania	86.4%	13.6%	85.6%	14.4%	85.5%	14.5%	85.4%	14.6%
Bulgaria	72.5%	27.5%	62.8%	37.2%	64.8%	35.2%	65.3%	34.7%
Total %	80.4%	19.6%	75.8%	24.2%	78.3%	21.7%	78.0%	22.0%
Total Obs	2579	758	1236	437	1434	440	1033	349

Source: Enterprise Survey and Financial Crisis Survey

Graph I Innovative x Noninnovative

(measuring innovation by introduction of new product/process in the 2004-2007 period)

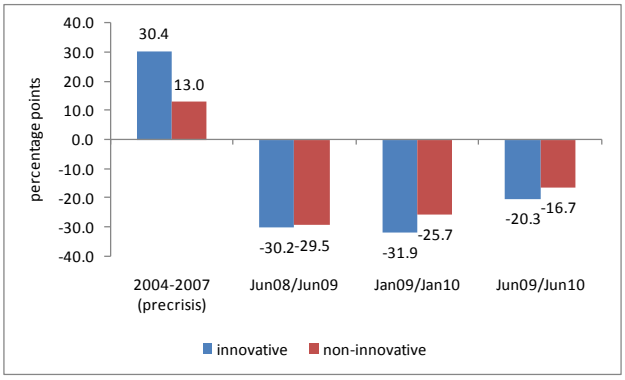

Table II – Explaining sales growth rate over time: complete results

(robust standard errors in parenthesis)

	Innovation measured as introduction of product/process		**Innovation measured by the performance of R&D**	
	Within estimator (1)	**Hausman-Taylor estimator (2)**	**Within estimator (3)**	**Hausman-Taylor estimator (4)**
June 08/June 09 (time2)	-37.738***	-37.939***	-41.024***	-41.925***
	(5.675)	(0.332)	(4.225)	(0.259)
Jan 09/Jan 10 (time3)	-38.147***	-39.292***	-39.084***	-40.006***
	(6.022)	(0.342)	(5.924)	(0.272)
June 09/June10 (time 4)	-27.095***	-29.283***	-27.919***	-29.087***
	(6.639)	(0.353)	(6.508)	(0.277)
Inov	.	13.150***	.	20.368***
	.	(0.368)	.	(0.458)
time2XInov	-13.022	-14.371***	-19.517	-19.208***
	(7.919)	(0.449)	(12.320)	(0.557)
time3XInov	-7.699	-9.300***	-16.079	-20.844***
	(9.543)	(0.457)	(13.642)	(0.554)
time4XInov	-9.301	-8.931***	-20.579	-23.206***
	(10.331)	(0.474)	(13.002)	(0.577)
Young	.	32.701***	.	31.333***
	.	(0.479)	.	(0.472)
time2XYoung	-38.439*	-31.321***	-36.751	-29.423***
	(22.726)	(0.649)	(22.315)	(0.639)
time3XYoung	-49.078**	-36.068***	-47.826**	-35.010***
	(22.462)	(0.698)	(22.305)	(0.686)
time4XYoung	-44.973**	-35.131***	-44.960**	-35.285***
	(21.999)	(0.694)	(21.675)	(0.681)
skill	.	2.804***	.	2.980***
	.	(0.255)	.	(0.253)
foreign	.	5.258***	.	5.660***
	.	(0.380)	.	(0.380)
small	7.275	8.245***	7.707	8.936***
	(9.549)	(0.223)	(9.816)	(0.220)
medium	9.684	15.621***	8.031	15.839***
	(10.856)	(0.358)	(11.271)	(0.354)
large	11.816	19.886***	9.895	19.644***
	(14.860)	(0.712)	(15.555)	(0.708)
Export	-6.686	-6.245***	-6.366	-5.931***
	(6.230)	(0.452)	(5.755)	(0.449)
WK.Int	0.046	0.051***	0.047	0.046***
	(0.079)	(0.002)	(0.076)	(0.002)

Turkey	.	23.208***	.	23.931***
	.	(0.458)	.	(0.458)
Romania	.	7.351***	.	8.497***
	.	(0.343)	.	(0.348)
Kazakhstan	.	22.330***	.	23.691***
	.	(1.117)	.	(1.111)
Hungary	.	13.556***	.	14.588***
	.	(0.416)	.	(0.425)
Latvia	.	-0.480	.	1.619***
	.	(0.405)	.	(0.410)
Lithuania	.	7.489***	.	10.081***
	.	(0.395)	.	(0.397)
Food	.	4.865***	.	5.216***
	.	(0.620)	.	(0.623)
Textiles	.	11.046***	.	10.784***
	.	(0.797)	.	(0.794)
Garments	.	-3.452***	.	-4.240***
	.	(0.748)	.	(0.744)
Chemicals	.	8.739***	.	8.672***
	.	(1.689)	.	(1.684)
Plastic and rubber	.	13.600***	.	13.740***
	.	(0.853)	.	(0.852)
Non metallic mineral products	.	-7.995***	.	-7.837***
	.	(0.905)	.	(0.906)
Basic metals	.	11.969***	.	12.116***
	.	(1.066)	.	(1.060)
Fabricated metal products	.	4.869***	.	4.863***
	.	(0.661)	.	(0.660)
Machinery and equipments	.	-4.882***	.	-5.358***
	.	(0.887)	.	(0.885)
Electronics	.	2.834**	.	0.111
	.	(1.334)	.	(1.313)
Construction	.	-1.106**	.	-3.311***
	.	(0.538)	.	(0.531)
Services of Motor Vehicles	.	-0.608	.	-2.037***
	.	(0.675)	.	(0.660)
Wholesale	.	7.164***	.	6.777***
	.	(0.459)	.	(0.460)
Retail	.	6.503***	.	6.329***
	.	(0.418)	.	(0.416)
Hotel and restaurants	.	1.283**	.	0.277
	.	(0.628)	.	(0.624)

Transport	.	7.010***	.	6.101***
	.	(0.558)	.	(0.556)
IT	.	1.044	.	1.929
	.	(1.202)	.	(1.200)
_cons	11.527	-13.428***	11.781	-11.594***
	(10.528)	(0.578)	(10.580)	(0.559)
N.obs	2527	2527	2530	2530
F/Chi2	18.16	88320.07	17.84	90996.47
Prob>F/Prob>Chi2	-37.738***	-37.939***	-41.024***	-41.925***

*** p<0.01, ** p<0.05, * p<0.1

Table III – Explaining sales growth rate over time: a panel data analysis including time interaction with innovative and export-orientation
(robust standard errors in parenthesis)

	Innovation measured as introduction of product/process	**Innovation measured by the performance of R&D**
	Hausman-Taylor estimator	**Hausman-Taylor estimator**
June 08/June 09 (time2)	-38.520***	-42.358***
	(0.327)	(0.257)
Jan 09/Jan 10 (time3)	-39.641***	-40.189***
	(0.337)	(0.271)
June 09/June10 (time 4)	-29.674***	-29.175***
	(0.349)	(0.275)
Inov	16.252***	24.783***
	(0.379)	(0.494)
time2XInov	-14.561***	-22.279***
	(0.462)	(0.610)
time3XInov	-14.318***	-24.522***
	(0.469)	(0.600)
time4XInov	-13.419***	-28.755***
	(0.487)	(0.624)
Young	32.533***	30.944***
	(0.476)	(0.470)
time2XYoung	-32.569***	-29.045***
	(0.642)	(0.636)
time3XYoung	-35.377***	-34.494***
	(0.690)	(0.684)
time4XYoung	-34.885***	-35.113***
	(0.685)	(0.678)
Inov_Export	-24.450***	-28.885***
	(0.815)	(1.081)
tine2XInov_Export	6.357***	19.087***

	(0.925)	(1.326)
tine3XInov_Export	40.997***	23.384***
	(0.946)	(1.322)
tine4XInov_Export	38.714***	32.766***
	(0.993)	(1.377)
skill	2.374***	2.535***
	(0.255)	(0.252)
foreign	4.183***	4.763***
	(0.378)	(0.376)
small	7.061***	8.211***
	(0.222)	(0.219)
medium	13.770***	14.520***
	(0.351)	(0.347)
large	18.676***	18.970***
	(0.706)	(0.704)
Export	3.413***	3.389***
	(0.382)	(0.322)
WK.Int	0.050***	0.048***
	(0.002)	(0.002)
Turkey	21.657***	22.832***
	(0.457)	(0.454)
Romania	8.340***	9.734***
	(0.342)	(0.347)
Kazakhstan	24.615***	25.116***
	(1.112)	(1.107)
Hungary	13.885***	14.916***
	(0.418)	(0.425)
Latvia	-0.597	1.433***
	(0.407)	(0.408)
Lithuania	8.273***	10.696***
	(0.397)	(0.397)
Food	5.367***	5.798***
	(0.620)	(0.619)
Textiles	10.173***	9.859***
	(0.799)	(0.792)
Garments	-5.191***	-6.676***
	(0.749)	(0.742)
Chemicals	5.379***	7.666***
	(1.689)	(1.678)
Plastic and rubber	11.265***	12.907***
	(0.859)	(0.850)
Non metallic mineral products	-7.799***	-7.399***

	(0.906)	(0.903)
Basic metals	7.092***	11.842***
	(1.078)	(1.056)
Fabricated metal products	4.440***	4.899***
	(0.664)	(0.658)
Machinery and equipments	-4.644***	-5.538***
	(0.889)	(0.883)
Electronics	4.048***	1.375
	(1.341)	(1.312)
Construction	0.192	-2.061***
	(0.535)	(0.524)
Services of Motor Vehicles	0.646	-0.718
	(0.673)	(0.654)
Wholesale	7.731***	7.267***
	(0.460)	(0.458)
Retail	7.113***	7.270***
	(0.416)	(0.410)
Hotel and restaurants	1.856***	0.666
	(0.630)	(0.621)
Transport	6.146***	4.867***
	(0.559)	(0.553)
IT	-0.050	1.996*
	(1.207)	(1.196)
_cons	-14.119***	-12.916***
	(0.578)	(0.556)
N.obs	2527	2530
F/Chi2	93177.13	92556.19
Prob>F/Prob>Chi2	0.0	0.0

*** p<0.01, ** p<0.05, * p<0.1

Table IV - Explaining sales growth rate over time: a panel data analysis excluding FCS wave 2 data (January2009-January 2010 period)
(robust standard errors in parenthesis)

	Innovation measured as introduction of product/process		**Innovation measured by the performance of R&D**	
	within estimator (1)	**Hausman-Taylor estimator** (2)	**within estimator** (3)	**Hausman-Taylor estimator** (4)
June 08/June 09 (time2)	-38.107***	-38.439***	-41.073***	-42.338***
	(5.935)	(0.360)	(4.388)	(0.278)
June 09/June10 (time 4)	-27.745***	-31.460***	-27.755***	-30.434***
	(7.451)	(0.383)	(7.476)	(0.298)
Inov	.	14.117***	.	23.180***
	.	(0.382)	.	(0.475)
time2XInov	-12.397	-14.727***	-19.452	-20.337***
	(8.482)	(0.491)	(13.330)	(0.606)
time4XInov	-9.892	-8.876***	-26.432*	-26.898***
	(11.326)	(0.512)	(13.463)	(0.619)
Young	.	30.053***	.	28.728***
	.	(0.478)	.	(0.470)
time2XYoung	-40.775*	-29.648***	-39.081*	-27.762***
	(23.819)	(0.695)	(23.338)	(0.682)
time4XYoung	-42.305*	-31.820***	-42.999*	-32.408***
	(24.450)	(0.731)	(24.063)	(0.717)
skill	.	-1.282***	.	-1.220***
	.	(0.261)	.	(0.260)
foreign	.	6.094***	.	6.573***
	.	(0.383)	.	(0.383)
small	6.749	5.711***	6.940	6.468***
	(11.973)	(0.251)	(11.985)	(0.247)
medium	6.099	10.026***	3.359	10.001***
	(13.463)	(0.391)	(13.737)	(0.386)
large	12.798	10.501***	9.607	9.688***
	(18.081)	(0.815)	(18.765)	(0.810)
Export	-6.760	-7.741***	-5.883	-6.171***
	(7.583)	(0.576)	(6.775)	(0.567)
WK.Int	0.040	0.052***	0.039	0.045***
	(0.102)	(0.003)	(0.097)	(0.003)
Turkey	.	29.853***	.	31.384***
	.	(0.644)	.	(0.629)
Romania	.	7.040***	.	8.927***
	.	(0.344)	.	(0.349)
Kazakhstan				
Hungary	.	9.806***	.	11.610***

	.	(0.417)	.	(0.427)
Latvia	.	-1.421***	.	1.556***
	.	(0.399)	.	(0.406)
Lithuania	.	6.227***	.	9.692***
	.	(0.392)	.	(0.396)
Food	.	2.912***	.	3.949***
	.	(0.670)	.	(0.674)
Textiles	.	3.818***	.	4.472***
	.	(0.890)	.	(0.886)
Garments	.	-7.539***	.	-8.390***
	.	(0.805)	.	(0.802)
Chemicals	.	7.274***	.	6.677***
	.	(2.223)	.	(2.210)
Plastic and rubber	.	7.025***	.	7.760***
	.	(0.924)	.	(0.922)
Non metallic mineral products	.	-6.717***	.	-5.022***
	.	(0.957)	.	(0.956)
Basic metals	.	18.297***	.	17.341***
	.	(1.227)	.	(1.222)
Fabricated metal products	.	0.897	.	1.187*
	.	(0.683)	.	(0.681)
Machinery and equipments	.	-7.735***	.	-8.382***
	.	(0.902)	.	(0.900)
Electronics	.	3.249**	.	-0.405
	.	(1.370)	.	(1.345)
Construction	.	2.895***	.	0.925*
	.	(0.558)	.	(0.551)
Services of Motor Vehicles	.	-2.248***	.	-3.298***
	.	(0.720)	.	(0.701)
Wholesale	.	4.501***	.	4.426***
	.	(0.466)	.	(0.467)
Retail	.	4.623***	.	5.155***
	.	(0.439)	.	(0.437)
Hotel and restaurants	.	0.675	.	0.129
	.	(0.635)	.	(0.630)
Transport	.	10.031***	.	9.167***
	.	(0.577)	.	(0.574)
IT	.	0.878	.	2.815**
	.	(1.181)	.	(1.179)
_cons	12.692	-7.388***	13.246	-6.721***
	(12.654)	(0.598)	(12.191)	(0.580)
N.obs	1776	1776	1778	1778
F/Chi2	18.17	65124.91	21.39	67845.01
Prob>F/Prob>Chi2	0.0	0.0	0.0	0.0

*** p<0.01, ** p<0.05, * p<0.1

Table V - Decomposing the total difference of sales growth rate between innovative and non-innovative firms: JMP results

Pre-crisis period (2004-2007)				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	6.61	4.37	10.90	-8.67
p10	5.19	2.02	10.54	-7.37
p25	2.80	-5.74	15.08	-6.54
p50	4.76	-4.16	15.26	-6.34
p75	13.30	-5.26	19.95	-1.39
p90	42.59	19.41	11.61	11.57
p95	22.72	-1.20	-3.82	27.74
Mean	12.79	-2.97	15.51	0.26
june08-june09				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	0.00	-5.69	2.50	3.19
p10	-8.30	-3.32	-7.97	2.99
p25	0.00	-1.34	-1.14	2.48
p50	0.00	0.01	0.43	-0.44
p75	-5.00	1.98	-2.01	-4.97
p90	3.70	3.62	0.61	-0.53
p95	2.10	2.89	0.90	-1.69
Mean	-0.87	-0.28	-0.73	0.15
January 09-January10				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	9.00	15.91	-10.88	3.97
p10	-9.10	4.44	-12.26	-1.28
p25	0.00	-1.31	2.04	-0.73
p50	0.90	4.06	0.11	-3.27
p75	3.50	6.51	-1.61	-1.40
p90	12.40	10.56	-0.65	2.49
p95	9.10	4.99	-0.95	5.06
mean	3.73	5.30	-1.48	-0.08
June09-June10				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	0.00	4.08	-0.21	-3.87
p10	10.00	5.54	5.23	-0.76
p25	10.00	-0.51	8.32	2.20
p50	4.00	-0.06	5.62	-1.56
p75	9.70	6.44	4.28	-1.02
p90	8.10	8.16	-0.23	0.17
p95	1.70	6.51	-1.44	-3.38

mean	8.21	3.40	5.13	-0.32

Table VI Decomposing the total difference of sales growth rate between young and older firms: JMP results

Pre-crisis period (2004-2007)				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	2.59	7.42	3.29	-8.12
p10	5.66	3.11	6.46	-3.91
p25	3.46	-0.61	9.56	-5.49
p50	6.30	1.92	11.37	-6.99
p75	49.00	10.80	50.04	-11.84
p90	79.79	12.71	53.77	13.31
p95	69.44	41.16	48.44	-20.17
Mean	28.35	8.16	24.15	-3.95
june08-june09				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	0.00	5.73	-7.31	1.58
p10	4.30	2.42	-2.93	4.81
p25	-4.30	1.99	-8.90	2.62
p50	0.00	4.08	-4.13	0.05
p75	5.00	5.37	0.18	-0.55
p90	5.60	-0.39	12.01	-6.02
p95	-6.70	-5.25	7.77	-9.22
Mean	0.26	2.27	0.17	-2.18
January 09-January10				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	10.00	5.43	-1.59	6.17
p10	1.40	-2.10	-9.65	13.15
p25	0.00	-0.83	-0.51	1.34
p50	-7.60	-1.32	-8.32	2.04
p75	-7.90	-7.56	4.71	-5.05
p90	6.70	-3.10	17.69	-7.89
p95	2.60	12.75	-1.87	-8.28
mean	-5.42	-0.88	-2.76	-1.78
June09-June10				
Percentile of the distribution	**Total Difference**	**Characteristics Effect**	**Return Effect**	**Residual Effect**
p5	8.30	5.32	-2.54	5.52
p10	-4.70	-8.21	-3.48	7.00
p25	-10.00	-11.71	3.23	-1.52
p50	-9.10	-9.47	-0.98	1.35

p75	-9.20	-14.63	15.74	-10.31
p90	-11.90	-15.49	14.70	-11.11
p95	-18.10	-5.89	59.71	-71.93
mean	-6.79	-8.03	4.29	-3.05