Persistence of innovation in times of crisis: An analysis of Italian firms

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May 31, 2018

Abstract

This paper investigates the extent to which innovation persistence unfolds in "times of crisis". By combining the extant literature with recent research on innovation along the downturn of business cycles, we expect that persistence hardly emerges in these times and that it is affected by the public support received by firms and by their business strategies. Drawing on the last three waves (2005-2013) of the MET survey on Italian firms, we find that innovation persistence is actually limited to process innovations, and to radical ones in particular. The detected persistence is reinforced by the public support firms receive for their ICT, while it is attenuated by that directed to their employment issues. Innovation persistence appears a business strategy itself, as firms seem to use it substitutively with that of intensifying their research and innovation efforts. Furthermore, innovation persistence appears limited to firms that face market competition through diversification strategies. Results suggest that a negative phase of the business cycle makes firm innovation relatively discontinuous, and that its persistence could trade-off with specific kinds of support and business strategies in the same situation.

Keywords: Innovation persistence; economic crisis; business cycle; policy support; business strategies.

JEL classification: O31; O32; O33

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‡This paper is based on the MET Survey (www.met-economia.it), kindly made available to the authors by the University of Ferrara.

1 Introduction

Innovation persistence has multiple economic implications. Not only can "success breed success" in innovation (Flaig and Stadler, 1994), making of it a source of competitive advantage. Innovation persistence can also account for patterns of industrial dynamics, in which incumbents can outplay new entrants, thus inhibiting the power of "creative destruction" typically exerted by innovation (Breschi et al., 2000).

For these reasons, innovation persistence has attracted a lot of attention in the academic literature. A consistent amount of studies have been published in the last twenty years, benefiting from the evolution of theoretical explanations, the increasing availability of new micro-data (in particular, innovation surveys and patents), and the development of more and more sophisticated econometric tools (in particular, in the domain of dynamic panels) (see Le Bas and Scellato (2014) for a review). The results of this large body of literature have added a lot to the knowledge on innovation persistence, but are far from conclusive about its occurrence. The persistence of firms in innovating depends on a number of internal and external factors related to their technological and organisational capabilities, and to the technological regime and market environment in which they operate, respectively (Antonelli et al., 2013; Triguero and Córcoles, 2013). Rather than simply dependent on the characteristics of the firms that have started to innovate – i.e. "past-dependent" – innovation is arguably contingent on the trajectory in which firms end out to place, following the co-evolution between their internal features and their external conditions – i.e. "path-dependent" (Antonelli et al., 2013).

The present paper shares this last point of view and adds that the context characteristics affecting innovation persistence comprehend also and above all the "conjuncture" stage of the business cycle. In particular, we maintain and aim at showing empirically two arguments. First of all, in times of crisis innovation persists to a quite low extent with respect to the array of innovation typologies in which firms could potentially involve (i.e. product vs. process ones). Second, in the same times innovation persistence is significantly moderated by the kind of public support firms receive and by the kind of business strategy they follow.

In developing our arguments, we follow up the extant literature on innovation persistence and combine it with some recent empirical studies on the relationship between innovation investments and economic cycle (Filippetti and Archibugi, 2011; Archibugi et al., 2013a,b). With respect to them, our paper has four elements of originality. First of all, we refer to a longer temporal window than recent survey-based (mainly CIS) studies (e.g. Archibugi et al. (2013b); Frenz and Prevezer (2012); Ganter and Hecker (2013)). Using data from three waves of the MET survey on Italy (see Section 3), we are capable of catching firms in: approaching the eve of the credit-crunch (first wave: 2005-2007), suffering from the Great Recession and the European sovereign-debt crisis (second wave: 2008-2010), and experiencing the entailed depression period (third wave: 2011-2013). Second, we go beyond the exclusive focus on innovation expenditures of previous studies on crisis and innovation (Filippetti and Archibugi, 2011; Archibugi et al., 2013a,b). In so doing, we reconcile them with the attention of persistence studies to different kinds of innovations (product vs. process, radical vs. incremental). Third, rather than comparing pre- with post-crisis innovation investments in a cross-sectional framework, we use a dynamic approach typical of the literature on persistence. In particular, we estimate a dynamic panel in which innovation is set to depend on its lagged value, and in which its "true" (vs. "spurious") dependence on the previous (endogenous) state is addressed by conditioning on its initial conditions (Ganter and Hecker, 2013; Raymond et al., 2010) and applying the Wooldridge (2002, 2005) correction. Fourth, we add to previous analyses of the moderating factors of innovation persistence (i.e. Ganter and Hecker (2013)) by looking at the moderating effect of the kind of public support firms benefit from and of their business strategies.

Our empirical analysis actually confirms that, with respect to the investigated sample of Italian firms, innovation persistence is mainly limited to process innovations and to radical ones in particular. The detected persistence is reinforced by the public support firms receive for their ICT, while it is attenuated by that directed to their employment issues. Innovation persistence appears a business strategy itself, as firms seem to use it substitutively with that of intensifying their research and innovation efforts. Furthermore, innovation persistence appears limited to firms that face market competition through diversification strategies. New policy and strategic implications can be drawn on these results.

The rest of the paper is structured as follows. Section 2 positions the paper in the relevant background literature. Section 3 presents the dataset and the econometric strategy. Section 4 illustrates the results, and Section 5 concludes.

2 Background literature

The analysis that we carry out in the paper combines two streams of literature. First of all, we refer to the large body of research on innovation persistence at the firm level, which deals with the influence of past on current firm's innovation (Le Bas and Scellato, 2014). From a theoretical point of view, there are three main explanations of this influence (see Ganter and Hecker (2013) for a schematic account of them). According to the *resource constraints* perspective, innovation persists if/when firms draw on the returns of previous (successful) innovation to attenuate the problematic financing of new innovation projects (risky and hardly collateralisable). The *sunk cost* perspective instead focuses on the barriers to entry and exit from innovation created by the costs of R&D. Setting up R&D facilities, recruiting and training R&D personnel, and positioning R&D within the organisation, actually have costs that become hard to recover once supported. Finally, the *competence-based* perspective interprets innovation persistence in the light of the knowledge that previous innovation makes available to the firm for the introduction of new one, thus reinforcing its innovation capacity over time.

The second stream of literature that we consider is about how innovation unfolds in front of an economic recession, following the burst of a deep crisis. With respect to the last economic recession, linked to the sub-prime mortgages crisis, a consistent amount of studies have actually investigated whether, and generally found that, its burst has dampened firms' innovation investments with respect to the pre-crisis period, but without looking for innovation persistence as such.[1] A notable exception is the study by Archibugi et al. (2013b), about the persistence of those (few) UK innovative firms that have increased innovation investments after the 2008 crisis (data come from three waves of the CIS for the UK (2002-2008)). In the theoretical background of their application the authors argue that, looking at the Schumpeterian accounts of the innovation process (Schumpeter, 1939),

[1] Among the others, see the evidence provided by Paunov (2012) on Latin American countries, by Cândido et al. (2016) on Brasil vs. Portugal, by Kanerva and Hollanders (2009) and, more recently, by Filippetti and Archibugi (2011) on European countries.

a regime of creative accumulation, with high innovation persistence, should be consistent with regular business times. Conversely, a regime of creative destruction, with low innovation persistence, would instead better fit with times of crisis. In contrast with this expectation, their econometric evidence obtains an opposite result, showing that "the cumulative, or persistent, nature of innovation activity tends to be more prominent in times of crisis compared to during ordinary times" (Archibugi et al., 2013b, p.311).

Quite interestingly, this result suggests that innovation persistence is actually dependent on the business cycle. However, that a negative downturn could actually strengthen innovation persistence, against theoretical expectations, appears hard to be generalized. When we go beyond the focus on innovation investments – structurally more persistent than innovation outputs (Le Bas and Scellato, 2014) – and we extend the analysis from the burst to the occurrence of "times of crisis", the Schumpeterian argument of a low persistence-innovation regime in these times appears more generally supportable. The three theoretical perspectives we have recalled at the beginning of this Section can help with that. For example, following the resource constraints perspective, given the higher credit obstacles firms suffer in times of crisis, they are less willing to re-invest in new innovations the returns eventually guaranteed by previously successful ones: indeed, this profitability could be more urgently and conveniently diverted from innovation towards more "ordinary" business activities. An attenuation of innovation persistence can also be accounted by thinking of the sunk-cost perspective and in the light of the competence-based one.[2]

Following the previous considerations, we claim that the Schumpeterian argument of the low cumulativeness of innovation in the aftermath of a negative shock has a manifold micro-foundation. On the same basis, we also develop a different argument about innovation persistence in times of crisis, which refers to the typologies of innovation firms could undertake in a persistent manner: in particular, product vs. process innovations, and radical vs. incremental ones. In "normal" times, firms are in principle capable of pursu-

[2]As for the former, during a recession, the loss of resources entailed by interrupting previous R&D investments could be lower than that ensuing from continuing them into new R&D projects: unfavorable market conditions could actually make the latter economically unviable. As for the latter, a crisis could represent the opportunity to "reset" previous competences and to build up new ones, whose innovation outcomes will be arguably too distant in time to get related with previous innovative outcomes.

ing persistence behaviors with respect to all of them, though to a different extent, given the heterogeneous relevance that resource constraints, sunk costs, and necessary competencies have with respect to them. For example, product innovations have been generally found more persistent than process ones (e.g. Antonelli et al., 2012). Although the evidence is more scanty, radical innovations have been also found more persistent than incremental ones, if not even exclusively (Ganter and Hecker, 2013).[3]

In times of crisis, however, the three mechanisms at stake can be, as we said, altered and this could entail a different scenario of persistent typologies of innovation than the previous one. In particular, we could expect that firms persist innovating in a more selective way, by focusing on the intertemporal development of those innovation typologies, which the crisis still leaves viable. In other words, the dampening effect that negative business conditions have on the mechanisms of innovation persistence, can induce an attenuation of it, not only at the intensive margin – according to the standard Schumpeterian argument – but also at the extensive one. Indeed, given their differences in terms of resource constraints, sunk costs and necessary competencies, the crisis arguably reduces the array of innovations with respect to which all these mechanisms can keep their role in linking past to present outcomes. What is more, the nature of the innovation typologies that can be found persistent in times of crisis does not necessarily coincide with those in normal business times. The crisis could actually entail an order of relevance among the three perspectives – resources, sunk costs, and competencies – which could make more persistent some innovation typologies that are less so in regular business times.

The typology of innovations that persist in times of crisis is also connected to the second argument of this paper, about the role of the public support firms receive and of the business strategies they follow. As far as the former is concerned, previous studies have shown that, in normal times, a financial help from the public sector is able to affect the firms' capacity to

[3]The first result can be interpreted with the more diffused sequential re-investments of extra-profits (resource constraints perspective) and with the superior R&D intensity (sunk cost perspective) of product with respect to process innovations. The second can instead be accounted by the higher risk of radical innovations (resource constraints), their higher reliance on R&D investments (sunk costs), and their higher opportunities of dynamics increasing returns (competencies) with respect to incremental ones.

persist in innovating, either by reducing or increasing it.[4] One way or the other, the moderating effect of the public support is expectedly relevant also and above all in times of crisis. In these times public authorities are actually asked to intervene counter-cyclically and restore the business and innovation activities, which a cyclical downturn generally compromises all across the economic system. Accordingly, the public support to firms' activities in times of crisis can/should be expected to be more diffused than in regular times and thus amenable to interfere more pervasively with the underlaying mechanisms of innovation persistence. Given our previous argument, about the typologies of persistent innovations in times of crisis, as much crucial is the consideration of the typology of public support, which data availability has prevented previous studies to retain. For example, a public intervention to the promotion of ICT will possible have effects mainly, if not even exclusively on the persistence of those process innovations that largely rely on them. Conversely, the public support to R&D activities could mainly moderate the persistent unfolding of product innovations, given their typically greater R&D intensity. In the light of these arguments, should the data permit it – as in our application – looking at different kinds of public support appears thus crucial.

The strategies that firms follow in their business activities represent another crucial moderator of innovation persistence to which the extant literature has paid attention. Recent studies have shown that, in normal times, persistent innovators are more likely to emerge when they pursue specific innovation strategies, for example, in terms of market vs. science orientation (Clausen et al., 2012). Furthermore, persistence has emerged reinforced by the combination of different innovation strategies, for example, of knowledge exploitation and knowledge exploration (Archibugi et al., 2013b). Innovation strategies are of upmost importance also in times of crisis, when they inevitably become part of the strategic behaviors through which firms can try to face these times. On the other hand, dealing with a negative phase of the business cycle generally requires firms to look for exit strategies also beyond the innovation realm, and possibly in combination with it (Bourletidis and

[4]The former case has been found by Ganter and Hecker (2013), and accounted with the fact that a public support makes funded firms less financially constrained and less in need to re-invest previous innovation returns. The latter has been documented by Peters (2009), and accounted with the additional resources that a public intervention can make available to firms for continuing their innovation over time.

Triantafyllopoulos, 2014): both within (e.g. efficiency improvements) and outside (e.g. delocalization choices) the firm boundaries (Antonioli et al., 2013). These business strategies would presumably have heterogenous effects on the resource constraints, sunk costs and competencies, on which innovation persistence depend, and will thus affect its unfolding. Accordingly, the consideration of their typology represents another crucial aspect to retain in the analysis, especially in order to disentangle their role for the specific typology of innovations that persist. Just to make an example, the search of efficiency gains through delocalization strategies is arguably more relevant for the persistence of process rather than product innovations. Also in this case, exploiting the availability of information about the business strategy that firms declare – another distinguishing feature of our database – becomes an important value added of the analysis.

3 Empirical application

Empirical studies on innovation persistence divide into the use of patent data and of innovation surveys or longitudinal innovation data (for a review of these methods, see Le Bas and Scellato (2014)). While patent-based studies have allowed the detection of interesting patterns of innovation persistence (e.g. Cefis, 2003), the use of patents remain exposed to important critiques (see Antonelli et al. (2012); Clausen et al. (2012); Raymond et al. (2010). In front of this criticism, our study makes use of repeated waves of innovation surveys and exploits the opportunities they offer in two respects (see Frenz and Prevezer, 2012). First of all, we are able to distinguish between different kinds of innovation, in particular, between product and process innovations, and to further decompose them into incremental vs. radical. Secondly, we can exploit the availability of information about a number of aspects that could reinforce or attenuate the impact of past on current innovation (Ganter and Hecker, 2013).

Our empirical analysis refers to a sample of Italian manufacturing firms, for which we have obtained data from three waves of the MET survey (http://www.met-survey.com/).[5] While specific to one national context, this survey has a unique coverage of information about a number of structural features and economic behaviours of the sampled firms in three periods

[5]See Brancati et al. (2015) for methodological insights on the survey.

of time around the last crisis, that is: 2005-2007 (wave 2008), 2008-2010 (wave 2011), and 2011-2013 (wave 2013). Among the other, the survey has a number of detailed questions about the innovation activities undertaken by the firms, as well as on the kind of support they received from the policy makers and of the strategic choices they have taken in carrying out their business activities in the focal periods. Furthermore, by including a wide set of ascriptive and descriptive information on the sample firms, the use of the MET survey makes it possible to retain heterogeneity in accounting for the issue at stake.

For each and every of the three considered waves of the MET survey, we have first cleaned the sample and referred to the population of manufacturing firms with at least 10 employees, amounting to around 10000 observation in each wave.[6] We have then merged the three MET waves of interest and obtained an unbalanced panel, which we have finally turned into a balanced one of 3300 (N*T) observations, by keeping only the firms that survived across the three waves – from the first (2008) to the last one (2013).[7] The resort to a balanced panel has a twofold motivation. First of all, the methodology we apply imposes us to consider observations over at least three periods of time (see Section 3.2 below). Secondly, our analysis aims at detecting the innovation persistence of firms that survived all over the crisis having been operative before of its burst. In brief, the potential bias induced in the estimates (Wooldridge, 2001)[8] does not hamper our analysis, since we select the surviving firms on purpose and we are interested in their own behaviour, without making inference on the entire firms population. Given the non-neutrality of the balanced panel choice on the innovation activity of the MET firms, the final target of our analysis – studying innovation

[6]A stratified random sampling is used for firms with fewer than two-hundred-fifty employees and a census is used for the population of firms with at least two-hundred-fifty employees. The stratum variables are the economic activity (based on the NACE classification), size (in terms of employees number) and geographical location (NUTS 2 level as statistical territorial unit). The potential problems generated by non-random attrition are likely to be negligible in our case because of the adopted sampling strategy: the lost firms in a wave are replaced by randomly selecting their pairs from the appropriate strata.

[7]In so doing, we have considered the attrition as an absorbing state.

[8]Focusing on a balanced panel in this setting we are generating a 'survivorship bias' (Raymond et al., 2015), which likely shift upwards the coefficient associated to the past innovation activity.

persistence and its relations with public support and business strategies for firms surviving over the crisis period – should be clearly retained.[9]

Tab. A1 in the Appendix reports the distributions of firms by sector and size of the final balanced working sample.

3.1 Variables

3.1.1 Dependent variables

The way we look for evidence of innovation persistence is by searching for the impact of previous on current innovation, with respect to three dependent variables: product innovations ($InnoProd$), process innovations ($InnoProc$), and the firm's resort to patent activity ($PatFile$). Furthermore, for each of the first two kinds of innovation typologies, we have added the consideration of radical ($InnoProdRad$ and $InnoProcRad$) vs. incremental changes ($InnoProdInc$ and $InnoProcInc$) in the respective domain.[10]

Following the experience of the CIS survey, the previous innovation variables are dummies, obtained by considering how the focal firms self-reported about their different innovation typologies on the basis of the Frascati Manual instructions.

3.1.2 Independent variables

The set of independent variables that we consider comprehends two kinds of covariates. First of all, we retain a number of variables that, according to the standard literature, could either predict and/or control for the occurrence

[9] Indeed, the information we lost (attrition is substantially a missing values problem) using a balanced panel seems to 'differ' from what we have retained with it. This has emerged by focusing on the innovating firms of the first survey (2008) and generating a dummy variable, *Attrition*, which takes value 1 for the firms that subsequently disappear in one or both of the next waves. Then we used this binary variable as it was a treatment variable, in order to compare the difference probability of attrition (which generate the selection bias) for treated and control groups as well as its relation with the propensity to innovate: the results converge in indicating that *Attrition* negatively influence the firms' probability to innovate in 2008. Hence, the surviving firms are generally more innovative and likely more persistent in innovation activities than those we miss.

[10] Their distinction is important as process innovations and innovations of an incremental nature may be considered as weak measures of persistence, given their more frequent occurrence over time.

of innovation in a certain period of time. In particular, the MET survey enabled us to include: R&D activities (RD), cooperation with universities and research organisations ($CoopUniResOrg$) and with firms ($CoopFirm$), internationalisation via exports (Exp), size, $Sector$ (NACE_Rev.2 two-digit), geographical location (Reg dummies), belonging to a business group ($Group$) as well as the turnover trend on the reference period for each wave ($TurnTrend$). With the exception of size, captured by the number of employees (Emp) and $TurnTrend$ – on a Likert scale over the triennium (1 strongly decreased, 2 decreased, 3 stable, 4 increased, 5 strongly increased) – all of the other variables are dichotomic.

We then plug among the regressors two set of variables that, as we said in Section 2, we expect to play an important role in moderating and/or conditioning the extent to which innovation persistence occurs. The first one, is a vector ($PubSup$) of six different kinds of public support, which the focal firms declared to have received in the relative period. These comprehend policy targets spanning from the specific support to research ($PubSuppRes$), technology transfer ($PubSuppInnoTr$) and to ICT ($PubSuppICT$), up to more general policy support to capital investments ($PubSuppPhisK$) and to employment ($PubSuppEmp$) (with $OtherPubSupp$ referring to other residual forms of support). The second is instead a vector of five business strategies that the sampled firms reported to have undertaken to carry out their business activities in the three waves, that is: the constitution of alliances ($Alliances$), the search of efficiency via investments ($NewInvestEff$), the intensification of R&D and innovation ($RDInno$), the diversification into new sectors of business ($Divers$), and other residual strategies ($OtherStrat$). All of these variables are dichotomic too (see Tab. A2 in the Appendix for the survey questions used to get information on public support and strategic actions).

Standard descriptive statistics of the used variables are reported in Table 1.

3.2 Econometric strategy

The econometric strategy that we follow consists of a set of dynamic probit models, which aim to account for the firm's probability to be an innovator in t conditional on its past innovation activity in $t-1$. More precisely, the model assumes the following structural form (Wooldridge, 2002, 2005):

$$Pr(Inno_{it} = 1|x_{it}, Inno_{i,t-1}.....Inno_{i,0}, c_i) = \Theta(x_{i,t}\beta + \gamma Inno_{i,t-1} + c_i) \quad (1)$$

In Eq.(1), *Inno* stands for each dependent innovation variables, **x** represents the vector of regressors described in the previous section, and **c** is a vector of firm-specific time invariant factors capturing heterogeneity (see Tab. 1).

Following Wooldridge, we can consider the latent variable model of Eq.(1):

$$Inno^*_{it} = x_{i,t}\beta + \gamma Inno_{i,t-1} + c_i + u_{it} \quad (2)$$

where c_i can be expressed as follow:[11]

$$c_i = \delta_0 + \delta_1 Inno_{i0} + x_i\delta_2 + a_i \quad (3)$$

In order to detect a state of "true" state-dependence in innovation, that is a situation in which, being γ significantly different from 0 in Eq.(2), firms reveal an actual innovation persistence, rather than a spurious one, for which $\gamma = 0$ (Raymond et al., 2010), in Eq.(3) we apply the correction proposed by Wooldridge (2002, 2005). In particular, we model the density for c_i on the basis of the initial condition of the dependent variables $Inno_{i0}$ (the value they assume in the first period we are observing) and of the averaged value over time of the x variables. This procedure is similar to that applied by Triguero and Córcoles (2013) and by Ganter and Hecker (2013) in the context of a dynamic non-linear random effect model. In the case of our dynamic random effect probit model, the use of a balanced panel, in which each firm is observed over three periods, ensures us that we are avoiding the risk of having a collapse of initial conditions and lagged dependent variables over the same period.

Assuming that, conditional on the initial condition $Inno_{i0}$ and on the x_i, in Eq.(3) a_i is normally distributed with zero mean and σ^2 variance, and that $Inno_{it}$ follows a probit model, by plugging Eq.(3) in Eq.(2) we finally obtain:

[11] In our latent variable model, we do not directly observe $Inno^*_{it}$ but we observe $Inno_{it} = 1$ when $Inno^*_{it} > 0$

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variables					
InnoProd_	3300	.363	.481	0	1
InnoProdRad_	3300	.27	.444	0	1
InnoProdInc_	3300	.248	.432	0	1
InnoProc_	3300	.297	.457	0	1
InnoProcRad_	3300	.223	.416	0	1
InnoProcInc_	3300	.215	.411	0	1
PatFile_	3300	.108	.311	0	1
Independent variables - x_{it}					
Controls					
Emp_	3300	125.602	295.949	10	5001
Group_	3300	.32	.467	0	1
Exp_	3300	.616	.486	0	1
TurnTrend_	3300	3.109	.912	1	5
RD_	3300	.353	.478	0	1
CoopUniResOrg_	3300	.082	.275	0	1
CoopFirm_	3300	.044	.204	0	1
Public support					
PubSupp_	3300	.201	.401	0	1
PubSuppRes_	3300	.046	.21	0	1
PubSuppInnoTr_	3300	.018	.131	0	1
PubSuppPhisK_	3300	.134	.34	0	1
PubSuppICT_	3300	.022	.147	0	1
PubSuppEmp_	3300	.019	.138	0	1
OtherPubSupp_	3300	.015	.121	0	1
Business Strategies					
Alliances_	3300	.182	.386	0	1
NewInvestEff_	3300	.169	.375	0	1
RDInno_	3300	.111	.314	0	1
Divers_	3300	.133	.339	0	1
OtherStrat_	3300	.559	.497	0	1

Number of observation given by: N*T, where T=1,2,3

$$Inno^*_{it} = x_{i,t}\beta + \gamma Inno_{i,t-1} + \delta_0 + \delta_1 Inno_{i0} + x_i\delta_2 + a_i + u_{it} \tag{4}$$

where u_{it} has a conditional standard normal distribution.

While Eq.(4) represents our benchmark model, by comparing its results with those obtained without the inclusion of the initial conditions, we can appreciate the extent to which the detected persistence is actually due to "path dependence", that is to say actual persistence, rather than to "past dependence" (Antonelli et al., 2013).[12]

After having corrected for the initial conditions, we augment our focal model by interacting the lagged value of innovation with the variables that, as we said, could have a role in attenuating, reinforcing and/or conditioning the occurrence of persistence. In so doing, we draw on and extend the methodology put forward by Ganter and Hecker (2013), through a focus on more detailed public support activities and firm business strategies. Quite intuitively, a positive (negative) sign of the interaction between these latter moderating variables and the lagged innovation variable would reveal that they reinforce (attenuate) innovation persistence, in case the lagged innovation variable keeps on its significance upon the inclusion of the interaction. Conversely, should this not occur, the effect of the same moderating variables would be of conditioning innovation persistence. In performing this last set of estimates, it should be retained that the inclusion of interaction terms brings about the usual problem of a potential "inflation" in the estimated variance due to multicollinearity. The relative large number of our covariates, also implied by the Wooldridge approach, coupled with the inclusion of interaction terms, thus calls for a careful check to detect multicollinearity. The two standard checks that we have applied to this scope – the variance inflation factor (VIF) and the condition number – do not show potential multicollinearity, when using as a rule of 'thumb' threshold above which multicollinearity can be a problem around 5 and 30, respectively,

4 Results

Before moving to the results of our estimates, it could be interesting to look at the transition probabilities of both innovators (value 1 of the relevant variables) and non-innovators (value 0) across the retained MET waves. Tab. 2 actually shows relevant traces of persistence in the innovation activities that

[12] This case implies "that there is substantial correlation between the unobserved heterogeneity and the initial conditions" (Wooldridge, 2005, p.51).

we observe. Persistence is definitively lager among the non-innovators (0, 0), the share of persistent innovators (1,1) is also remarkable: spanning from about 27% (*InnoProcInc*) in the first sub-period to 75% (*InnoProd*) in the second sub-period.

Table 2: Transition probabilities: persistent behaviours

	Two transitions 2005-2007→2008-2010→2011-2013		First transition 2005-2007→2008-2010		Second transition 2008-2010→2011-2013	
	1,1	0,0	1,1	0,0	1,1	0,0
	%	%	%	%	%	%
InnoProd	54.66(469)	85.02(1141)	41.37(218)	80.28(460)	75.83(251)	88.56(681)
InnoProdRad	44.88(293)	88.68(1371)	30.50(129)	84.93(575)	71.00(164)	91.60(796)
InnoProdInc	58.90(288)	90.07(1451)	34.69(128)	87.41(639)	72.73(160)	92.27(812)
InnoProc	49.02(349)	87.23(1298)	35.52(157)	82.83(545)	71.11(192)	90.72(753)
InnoProcRad	43.25(237)	91.40(1510)	30.53(109)	88.96(661)	67.02(128)	93.40(849)
InnoProcInc	43.05(220)	89.93(1519)	27.19(87)	86.67(676)	69.63(133)	92.74(843)
PatFile	47.21(127)	96.84(1870)	36.09(87)	95.81(892)	66.00(66)	97.80(978)

However, the matrices confirm the view of the crisis as a momentum of creative destruction in terms of innovation. Only less than half of the initial innovators do not give up in front of its burst (first sub-period transition) and innovation actually appears pro-cyclical: more than 50% of the initial innovators move from 1 to 0 and only about 20% of the initial non-innovators react to the crisis by innovating. The share of persistent behaviours increases when firms move within the crisis, showing that the business climate appears more suitable to maintain innovation when it stabilizes. Also the share of persistent non-innovators increases even further when the cycle stabilizes: reacting to the crisis by innovating possibly fades away when the shock gets assimilated by the economic system.

The same results reveals only partially consistent with the extant literature when the specific kind of persistent innovation is considered. Although the MET survey refers to patents filing rather than to patent counts, as in the literature, according to expectations (see the review by Le Bas and Scellato (2014)), the share of persistent declared innovators is higher than that of persistent patent filers only in the second sub-period transition. Still according to the literature, the share of persistent innovators appears higher with respect to product rather than process innovations across the three retained transitions. In addition, persistent incremental innovators appears more numerous than persistent radical ones, as it would be expected, only with respect to product innovations. When we look at process innovators, instead, somehow unexpectedly, persistent radical innovators are more numerous than incremental ones, with the only exception of the second subperiod transition.

Overall, a tendency to persist in the same innovative (and non-innovative) behaviour across time and innovation types seems to be present in our sample of Italian firms. Whether this tendency is actually a sign of an actual persistence is left to the econometric analysis, whose results are reported in Tables 3-5.

Table 3 presents the results of the (random effect) dynamic probit of the baseline model - that is, without interaction terms - when the Wooldridge correction is applied to account for initial conditions. First of all, let us notice that, while persistence appears pervasive across all the innovation typologies in the uncorrected model, which we report in the Appendix (Tab.A3), it reduces to few out of the seven typologies when the initial conditions (Wooldridge correction) are controlled for, that is: process innovations ($InnoProc$), in general (5% level of significance) and radical ($InnoProcRad$) (1%) in particular, while that of radical product innovations ($InnoProdRad$) has a lower level of significance (10%).

Table 3: Firm's probability to be an innovator in t conditional on innovation in $t-1$ (Wooldridge approach for initial conditions)

	InnoProd	InnoProdRad	InnoProdInc	InnoProc	InnoProcRad	InnoProcInc	PatFile
Lagged dependent variables and Initial Conditions							
LagInnoProd	0.150						
	(0.173)						
ProdInitCond	1.030***						
	(0.263)						
LagInnoProdRad		0.314*					
		(0.190)					
ProdRadInitCond		0.435*					
		(0.240)					
LagInnoProdInc			0.097				
			(0.205)				
ProdIncInitCond			1.656***				
			(0.311)				
LagInnoProc				0.440**			
				(0.188)			
ProcInitCond				0.752***			
				(0.251)			
LagInnoProcRad					0.676***		
					(0.196)		
ProcRadInitCond					0.761***		
					(0.268)		
LagInnoProcInc						0.290	
						(0.209)	
ProcIncInitCond						0.810***	
						(0.279)	
LagPatFile							0.380
							(0.407)
PatInitCond							4.648***
							(1.585)

Table 3: Continued

	InnoProd	InnoProdRad	InnoProdInc	InnoProc	InnoProcRad	InnoProcInc	PatFile
PubSuppRes	0.210	0.481	-0.530	-0.340	-0.424	0.086	2.417**
	(0.637)	(0.523)	(0.684)	(0.619)	(0.555)	(0.616)	(1.013)
PubSuppInnoTr	1.288*	0.286	2.431**	-0.435	-0.452	-0.169	-1.532
	(0.729)	(0.701)	(1.010)	(0.897)	(0.897)	(0.945)	(1.824)
PubSuppPhisK	1.188***	1.099**	0.147	0.634	0.673*	0.450	0.671
	(0.441)	(0.431)	(0.447)	(0.391)	(0.383)	(0.408)	(0.753)
PubSuppICT	0.568	-0.010	1.997**	1.886***	1.628**	2.074***	1.367
	(0.817)	(0.681)	(0.790)	(0.588)	(0.681)	(0.660)	(1.495)
PubSuppEmp	0.028	-0.786	1.314**	0.207	1.037	0.017	-1.469
	(0.920)	(0.718)	(0.638)	(0.665)	(0.772)	(0.671)	(1.556)
PubSuppOther	1.171	0.952	1.885*	1.115	1.328*	1.652*	0.407
	(0.870)	(0.909)	(0.963)	(0.737)	(0.703)	(0.930)	(0.951)
Alliances	0.609	0.265	0.650	0.606*	0.390	0.395	-0.437
	(0.525)	(0.467)	(0.524)	(0.368)	(0.352)	(0.438)	(0.796)
NewInvestEff	0.108	-0.046	0.036	-0.156	0.187	-0.751*	-0.250
	(0.409)	(0.376)	(0.445)	(0.358)	(0.364)	(0.385)	(0.759)
RDInno	0.371	0.073	0.327	0.087	-0.103	0.175	0.096
	(0.425)	(0.402)	(0.472)	(0.375)	(0.374)	(0.435)	(0.768)
Divers	-0.654	-0.484	-0.418	0.284	0.380	0.071	-0.219
	(0.572)	(0.518)	(0.573)	(0.430)	(0.442)	(0.464)	(0.887)
StratOther	-0.480	-0.348	-0.445	-0.642*	-0.352	-0.885**	-0.545
	(0.372)	(0.346)	(0.419)	(0.346)	(0.347)	(0.398)	(0.728)
Cons	-5.211***	-4.212***	-5.838***	-3.714***	-3.763***	-4.584***	-11.670***
	(0.828)	(0.765)	(0.951)	(0.710)	(0.690)	(0.823)	(2.986)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\overline{x}_i$ (x_{it} averaged over time)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2200	2200	2200	2200	2200	2200	2200
sigma_u	2.168	1.863	2.272	1.850	1.576	2.033	3.553
rho	0.825	0.776	0.838	0.774	0.713	0.805	0.927
chi2(df)	128.289(50)	138.657(50)	117.548(50)	141.694 (50)	140.015(50)	111.859(50)	73.379(50)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This is a first interesting result of our application, which suggests that innovation is more frequently past- rather than path-dependent, also and above all in times of crises.

The same evidence confirms our expectations about innovation persistence to be a limited phenomenon when the aftermath of the last crisis is retained. Going beyond its burst, in accordance with the Schumpeterian view, the cumulativeness of innovation in times of crisis is a limited phenomenon, which pertains to only few typologies of it. In the case at stake, firms seem to persist in innovating over a specific type of innovation: radical process innovation. From an empirical point of view, this result appears consistent with the pivotal role that innovations in industrial processes (e.g. engineering and reverse engineering) have been found to have in the Italian systems of innovation since long (Malerba, 1993). Keeping a constant attention to the introduction of remarkable novelties in production/distribution processes appears a strategy that Italian firms are willing and capable to follow also in front of times of crisis. From a theoretical point of view, instead, this result finds only limited support in the three "standard" perspectives of innovation persistence that the literature has recognized, casting doubts about their invariant holding in times of crisis. As process innovations are usually less resource constrained (e.g. less risky) than product ones, one should expect them to be less persistent than their product companion (see Ganter and Hecker (2013) on this point), even in times of crisis. Similarly, given that process innovations arguably entail lower up-front, irrecoverable costs than product innovations - e.g., they are usually less R&D intensive than the latter - we could have expected less persistence for process innovation also during an economic recession. In contrast with the other two, the competence-based perspective could instead provide a conceptual interpretation for our results. From a cognitive point of view, given the tacit nature of the knowledge that characterises process innovation, its embeddedness in the physical stock of the firm and in the organisational routines of its production processes, one could think that its intrinsic cumulativeness is not disrupted by the economic crisis. Also in times of crisis, the firm could find difficult to get rid of a process kind of knowledge – for its nature "sticky" and hardly separable from the knowledge-base of the firm – in order to move on a different learning pattern.

Coming to the second part of our empirical application, related to the role of public policies and business strategies in innovation persistence, some preliminary evidence is provided by Table 3.[13]

First of all, among the different kinds of public support that we consider, the intervention in favor of firms' physical capital acquisitions ($PubSuppPhisK$) turns out significant with respect to the firm's introduction of product innovations ($InnoProd$) and of their radical forms in particular ($InnoProdRad$). Unlike radical ones, incremental product innovations seem to benefit from the public support to technological transfer ($PubSuppInnoTr$), which firms could use to draw on external knowledge in improving their products, and from the support to employment ($PubSuppEmp$) too, as this could help them with the use of human capital for the same scope. As expected, ICT policies ($PubSuppICT$) are mainly related to process innovations ($InnoProc$), which often occurs through the introduction of digitalisation and automation practices in the production process. Finally, and quite interestingly, the support to research and development ($PubSuppRes$) seems to exert its effect only on its closer outcomes, that is patent filing ($PatFile$).

While the picture of the results in terms of public support appears reach and consistent, the ones we got in terms of firm business strategies are quite disappointing. No one of the specific strategies that the MET survey enables us to capture seem to have a direct effect on the innovation behaviours of our sample of Italian firms. Still, in spite of that, we will have to check for their influence as moderating factors of innovation persistence in what follows.

In this last respect, Tab.4 reveals interesting results. Of course, as process innovations (general and radical) are the only ones that we found persistent, along with radical product innovations (but at a low significance level), moderation effects are considered only with respect to them.

First of all, the result obtained by Ganter and Hecker (2013) about the negative moderating role of public financing support in general,[14] gets only partially confirmed in times of crisis and enriches of interesting granularity. On the one hand, the firms' receipt of a public support exerts such a negative moderation effect only with respect to radical process innovators ($InnoProcRad$), and only when a specific kind of support is considered to

[13]Because of space constrains, in the same table we have omitted to report the results about the other controls. Full results are available from the authors upon request.

[14]The authors interpreted this result by referring to the resource constraints perspective, claiming that the support makes firms less financially constrained and thus less persistent.

job creation and training: in brief, a public support to the firm employment ($PubSuppEmp$). While the resource constraints perspective could have a role in accounting for this result – in the end, the support possibly alleviates the firm's need of reinvesting the results of previous innovations into new ones, irrespectively from its aim – the specific nature of the policy introduces another interesting interpretation: firms try to increase the benefit from this support by reducing the possible job destruction effects that a high persistence in process innovation could entail, which is understandable in times of crisis, when employment is a crucial issue. On the other hand, the result by Ganter and Hecker (2013) gets reversed – i.e., the moderation of past innovation is positive, instead of negative – with respect to process innovations in general ($InnoProc$), when the public support to the ICT of the firms ($PubSuppICT$) is considered. This is another interesting result that, in our view, could be read through the competence-based perspective. In times of crisis, firms become more capable of drawing on previous process innovations, and of building new ones up on them, when they get a public support to the endowment of those technologies – that is, ICT – on which process innovations mostly rely nowadays.

Table 4: Firm's probability to be an innovator in t conditional on innovation in $t-1$ (Wooldridge approach for initial conditions):
lagged dependent variables interacted with Public Support variables

	InnoProdRad	InnoProc	InnoProcRad
LagInnoProdRad	0.290		
	(0.206)		
ProdRadInitCond	0.437*		
	(0.242)		
LagInnoProc		0.340*	
		(0.203)	
ProcInitCond		0.758***	
		(0.252)	
LagInnoProcRad			0.638***
			(0.206)
ProcRadInitCond			0.751***
			(0.269)
LagInnoProc*PubSuppICT		2.478**	
		(1.236)	
LagInnoProcRad*PubSuppEmp			-1.651**
			(0.809)
_cons	-4.234***	-3.711***	-3.770***
	(0.776)	(0.717)	(0.694)
x_{it}: Controls, Time, Sector and Geographical dummies, Public Support and Strategies variables	Yes	Yes	Yes
$\overline{x}_i$ (x_{it} averaged over time)	Yes	Yes	Yes
N	2200	2200	2200
sigma_u	1.893	1.889	1.582
rho	0.782	0.781	0.714
chi2(df)	141.929(56)	139.314(56)	149.437(56)

Standard errors in parentheses; Only significant interactions are reported
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1 and 2 show interesting results about the relative size of the moderating effects we have detected in terms of policy. In particular, the public support to ICT ($PubSuppICT$) appears to affect the focal form of innovation persistence to a greater extent (in absolute values) than that to employment ($PubSuppEmp$). With respect to the latter, the recipients are less persistent than non-recipient firms, but with only slightly different average partial effects, of -0.15% and 0.09%, respectively. Conversely, with respect to the ICT support, the recipients show an average partial effect of lagged innovation on the current innovation of 0.42%, against one of only 0.05% for non-recipient firms.

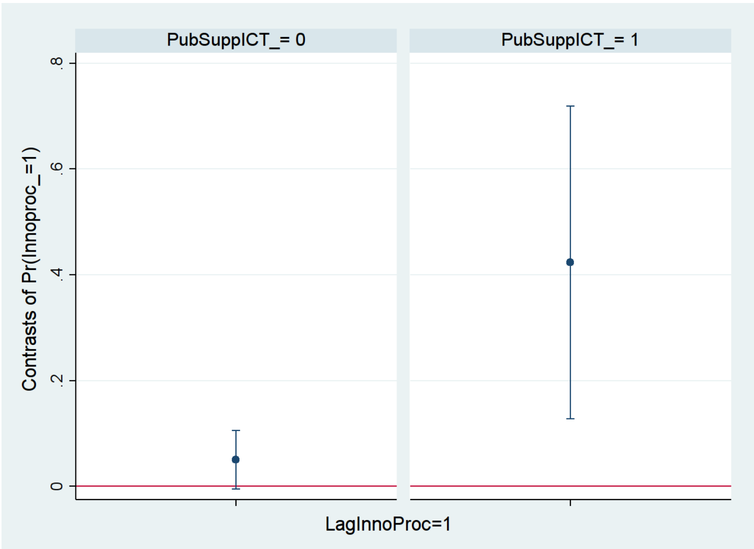

Figure 1: Process Innovation persistence with (right) or without (left) public support in ICT

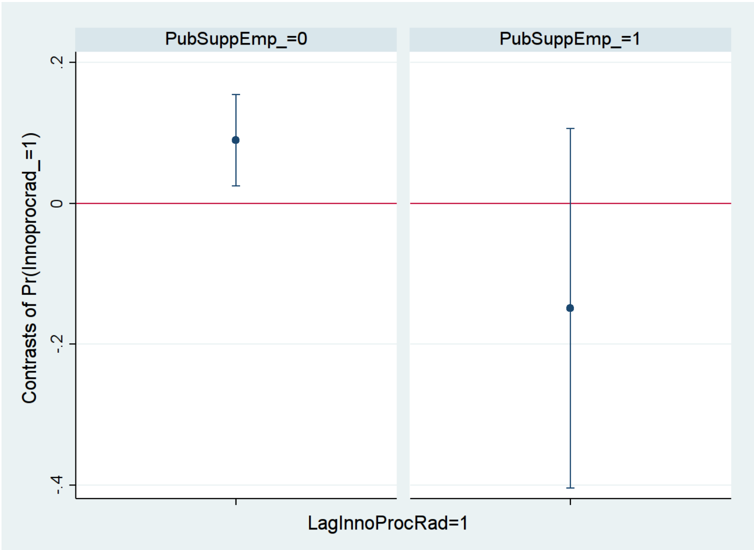

Figure 2: Radical Process Innovation persistence with (right) or without (left) public support for employment

As far as the role of the business strategies is concerned (Tab.5), our results extend previous evidence about their conditional effect on innovation persistence: innovation persistence is limited to innovators with specific strategies. While previous studies have found support of this argument in terms of dedicated innovation strategies – e.g. explorative, R&D-based, and the like (e.g. Archibugi et al., 2013a; Clausen et al., 2012) – our evidence extends the result to more general business ones, with which firms carry out their economic activities at large. First of all, let us observe that, in times of crisis, innovation persistence appears a kind of innovation strategy *per se*, which the firms of our sample seem to use substitutively with respect to other innovation strategies. This is suggested by the fact that firms adopting the most innovation-based of the available strategies – i.e., "intensifying R&D and innovation efforts" ($RDInno$) – are the only ones for which the lagged interacted values of innovation are significant and with a negative effect on current innovation.In other words, firms that follow an "intensive" innovation strategy – amounting to a general intensification of their innovation efforts – appear to count less on a "persistence" innovation strategy – amounting to build future innovations on previous ones.

Finally, persistence in process innovations (in general terms, $InnoProc$) in times of crisis appears "reserved" to the Italian firms of the sample that have declared to pursue a strategy of diversification of their business activities (*Divers*). When the interaction between this strategy and the lagged value of process innovation is considered, the latter actually loses significance and the former is instead significant with a positive sign. Quite interestingly, in order to cumulate on previous innovations in their production processes, at least in our focal period, firms apparently need to integrate the relative "internal" knowledge with the "external" one, possibly accruing to them by diversifying into new sectors, which could provide new innovation opportunities: a tentative explanation that still draws on the competence-based perspective.

Table 5: Firm's probability to be an innovator in t conditional on innovation in $t-1$ (Wooldridge approach for initial conditions):
lagged dependent variables interacted with Business Strategy variables

	InnoProdRad	InnoProc	InnoProcRad
LagInnoProdRad	0.745*		
	(0.391)		
ProdRadInitCond	0.486*		
	(0.263)		
LagInnoProc		0.411	
		(0.437)	
ProcInitCond		0.788***	
		(0.279)	
LagInnoProcRad			0.917**
			(0.432)
ProcRadInitCond			0.748***
			(0.288)
LagInnoProdRad*RDInno	-1.511***	-0.922**	-1.075***
	(0.433)	(0.434)	(0.409)
LagInnoProc*Divers		1.034**	
		(0.491)	
_cons	-4.672***	-4.027***	-4.084***
	(0.865)	(0.807)	(0.762)
x_{it}: as in Tab.4	Yes	Yes	Yes
Public Support and Strategies variables			
$\overline{x}_i$ (x_{it} averaged over time)	Yes	Yes	Yes
N	2200	2200	2200
sigma_u	2.034	2.110	1.713
rho	0.805	0.817	0.746
chi2(df)	130.798(55)	138.451(55)	147.939(55)

Standard errors in parentheses; Only significant interactions are reported
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

With respect to both of these significant strategies, it is still worth observing the change in the average partial effect of past on current innovation that they induce. Figg. 3 to 6 show that, in absolute values, the two strategies exert not too dissimilar moderating effects on the relevant forms of innovation persistence.

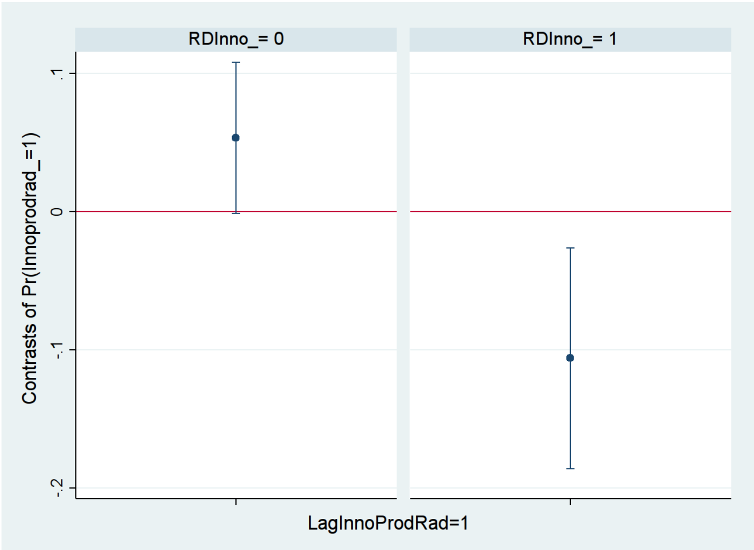

Figure 3: Radical Product Innovation persistence with (right) or without (left) RD_Inno_ business strategy

An R&D intensification strategy (*RDInno*) reduces the persistence of: radical product innovations of about 15% (from 0.05 for firms not pursuing the strategy to -0.10 for firms adopting this strategy); process innovations of about 9% (from 0.06 to -0.03); radical process innovations of about 11% (from 0.10 to -0.01). On the other hand, diversification strategies (*Diver*) show a positive moderating effect on process innovation, but with a relatively similar magnitude. The discrete change in the probability to currently innovate, being an innovator in the past, is augmented by around 13% for firms adopting this strategy (from 0.03 for those that do not pursue the strategy to 0.16 for those pursuing the strategy).

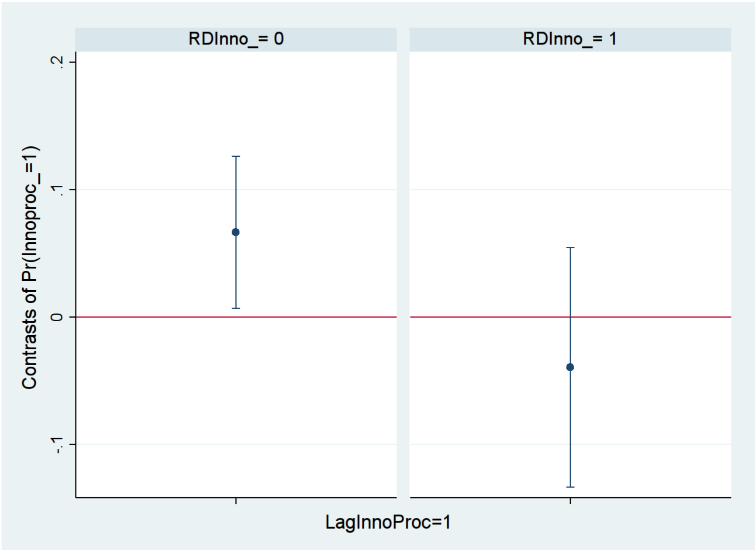

Figure 4: Process Innovation persistence with (right) or without (left) RD_Inno_ business strategy

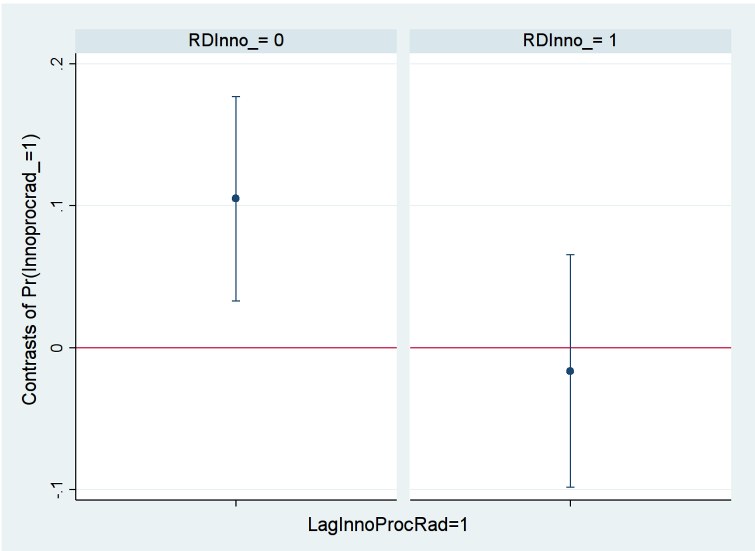

Figure 5: Radical Process Innovation persistence with (right) or without (left) RD_Inno_ business strategy

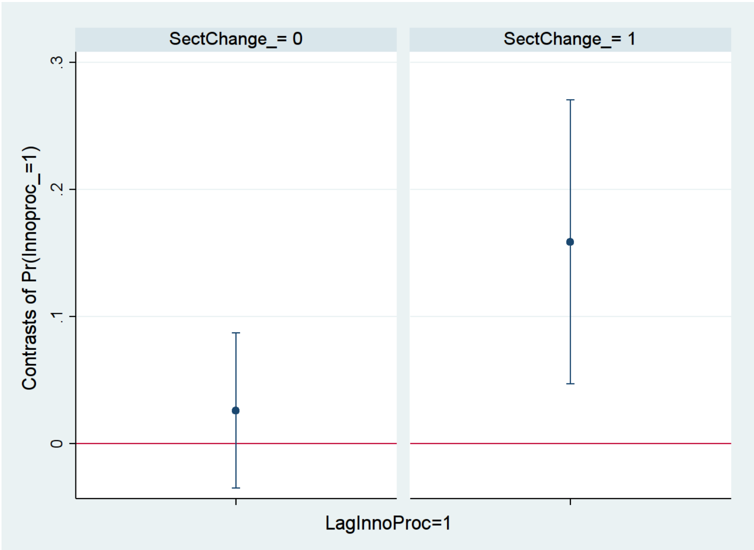

Figure 6: Process Innovation persistence with (right) or without (left) Divers_ business strategy

All in all, not only is innovation persistence limited in times of crisis, but it appears also very sensitive to the specific kind of public support firms receive and on the specific kind of business strategy they follow in the same times. Given the pervasive and crucial role that both of these issues have in times of crisis, their implications in terms of innovation persistence represent an additional element that should at least inform their adoption.

5 Conclusions

This study has investigated the innovation persistence of Italian manufacturing firms during an idiosyncratic period of the business cycle, marked by their entrance and passage through times of economic crisis. Connecting the extant literature on innovation persistence with that on innovation and crises we have argued that the analysis at stake should retain the various innovation domains (product vs. process, incremental vs. radical) in which firms can involve, as in times of crisis their persistence could be limited to some of them. Furthermore, we have also claimed that in the same kind of period public policies and firm strategies can be expected to have a significant moderation effect on the impact of past on current innovation.

By using three waves of the MET survey on Italian firms, we have provided novel evidence on innovation persistence, by estimating a set of dynamic probits corrected for the initial conditions, in order to disentangle past- from path-dependence in innovation. Indeed, the MET survey contains a unique synthesis of CIS-like questions on firm innovation, business strategies and policy receipt, which allow us to carry out such an original analysis.

The observation of transition matrices suggests that innovation persistence actually tends to decrease when firms enter the slowdown phase of the business cycle. Several factors, ranging from the drop of the aggregate demand to the reduction of economic agents' confidence, arguably account for this evidence. As expected, uncertainty and instability of the business cycle seems to lower the innovation persistence of Italian firms, which however tends to remerge when cycle stabilizes, although along an unfavourable path.

The econometric analysis supports this transitional evidence, showing that, when controlling for the initial condition problem in the dynamic model, true innovation persistence hardly occurs over periods of economic crisis, being limited to some innovation typologies only. In particular, in the retained temporal period, Italian firms seem to persist only in their process kinds of innovations and, somehow unexpectedly, only in their radical typologies. A competence-based approach to innovation persistence appears the most suitable theoretical perspective to account for this result, which appears also explainable by the structural characteristics of the Italian national system of innovation.

Interesting results do also emerge from the analysis of the persistence moderating role of public policies and firm business strategies. Public support to firms actually attenuate the scarcity of financial resources available to them for the sake of innovation, making persistence less necessary to deal with it. However, this occurs only in the case of an employment directed support, while ICT public policies do increase innovation persistence. Similarly, the moderating role of business strategies emerges highly specific too: in a sort of substitution effect, intensifying R&D and innovation efforts reduces the impact of past on current innovations, while persistence gets amplified by firms, which follow a diversification kind of strategy. Since the public support to firms in its diverse connotations affects persistence selectively and differently, the policy makers should be concerned about the heterogeneous effects on persistence of public support. Supporting innovation enabling factors, such as ICT, can be a viable strategy to increase the probability of innovation persistence. Conversely, a support to employment should be picked up by retaining that it could clash with innovation persistence. In the same vein, the managerial implications of our results are based on the heterogeneous effect of business strategies as moderating factors: managers should retain that the choice of the business strategies they implement could condition their capacity of persisting in innovation, and that some strategies may even generate a substitution effect with respect to innovation persistence.

All in all, not only is innovation persistence limited in times of crisis, but it appears also very sensitive to the specific kind of public support firms receive and on the specific kind of business strategy they follow in the same times. Given the pervasive and crucial role that both of these issues have in times of crisis, their implications in terms of innovation persistence represent an additional element that should at least inform their adoption.

The paper is not free from limitations. A first one comes from the temporal extension of the data at our disposal, which has induced us to work with a balanced panel of firms, having survived over the three periods we have retained in the analysis. While it has sound methodological motivations, this choice makes of our analysis a "special" case of innovation persistence in times of crisis, revealed by firms that have survived to its burst and its diffusion. As this imposed sample selection could have artificially inflated the extent to which firms could have actually persisted, the very limited evidence of it we have detected even in the presence of such a bias appears however revealing of our research arguments. A second limitation concerns the survey-based way in which information about innovation, public policies and business strategies have been collected: problems of response biases and of possibly endogeneity could affect the relative variables, which only a merge between MET and other secondary data – by now unfortunately impracticable – could help address.

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Appendix

Table A1: Distribution by Sector, Geographical Location, Size

Sector		Macro Region		Size	
	%		%		%
Food	5.70	Northern Italy	46.55	Small	50.06
Textile	13.15	Center Italy	29.73	Medium	36.55
Wood	8.61	Southern Italy and Isles	23.73	Large	13.09
Paper	5.09				
Chemicals	11.36				
Metallurgy	13.97				
TranspMach	9.94				
Machinery	13.45				
ElectrApp	9.52				
OtherInd	9.21				

Table A2: The following questions were asked to retrieve information on firms' business strategies and public support

Which kind of business strategies are adopted?	
Business Strategy	Variable name
	(Type: binary(0,1))
1. Alliances with other firms	Alliances
2. New investments to improve efficency	NewInvestEff
3. Intensified activities in R%D and Innovation	RDInno
4. Concentration or shift toward rewarding sectors or diversification	Divers
5. Other	OtherStr

Which kind of public support did you receive ?	
Type of support	Variable name
	(Type: binary(0,1))
1. Public support to research projects	PubSuppRes
2. Public support to technological transfer and innovation	PubSuppInnoTr
3. Public support to acquire physical capital	PubSuppPhysCap
4. Public support to ICT	PubSuppICT
5. Public support to employment and training	PubSuppEmp
6. Other	OtherPubSupp

Table A3: Firm's probability to be an innovator at t conditional on innovation at $t-1$ (no Woolridge correction)

	InnoProd	InnoProdRad	InnoProdInc	InnoProc	InnoProcRad	InnoProcInc	PatFile
PubSuppRes	0.761*	0.077	0.575	0.195	-0.105	0.390	0.349
	(0.406)	(0.336)	(0.371)	(0.373)	(0.323)	(0.383)	(0.400)
PubSuppInnoTr	0.520	-0.017	1.002*	-0.463	-0.224	-0.065	-0.003
	(0.598)	(0.596)	(0.539)	(0.600)	(0.572)	(0.635)	(0.805)
PubSuppPhisK	0.365	0.497*	-0.043	0.516**	0.556***	0.451*	0.184
	(0.260)	(0.265)	(0.237)	(0.236)	(0.213)	(0.255)	(0.298)
PubSuppICT	0.293	-0.132	0.985**	0.611	0.552	0.848*	-0.320
	(0.513)	(0.465)	(0.482)	(0.441)	(0.433)	(0.484)	(0.541)
PubSuppEmp	-0.003	-0.263	0.560	-0.031	0.334	-0.006	0.165
	(0.615)	(0.525)	(0.487)	(0.481)	(0.503)	(0.482)	(0.658)
PubSuppOther	0.275	0.310	0.283	0.993*	1.021**	1.019	-0.441
	(0.596)	(0.578)	(0.652)	(0.548)	(0.493)	(0.655)	(0.727)
Alliances	0.151	-0.071	0.142	0.584**	0.426*	0.356	0.159
	(0.311)	(0.306)	(0.305)	(0.270)	(0.253)	(0.305)	(0.360)
NewInvestEff	0.316	0.115	0.251	0.066	0.395*	-0.490*	0.083
	(0.250)	(0.249)	(0.245)	(0.226)	(0.214)	(0.267)	(0.294)
RDInno	0.310	0.208	0.233	0.064	0.040	0.123	0.159
	(0.258)	(0.261)	(0.258)	(0.241)	(0.230)	(0.275)	(0.309)
SectChange	-0.256	-0.192	0.132	-0.016	0.057	-0.062	0.002
	(0.312)	(0.306)	(0.295)	(0.271)	(0.260)	(0.300)	(0.374)
StratOther	-0.103	-0.227	-0.023	-0.319	-0.090	-0.482*	-0.349
	(0.249)	(0.248)	(0.260)	(0.240)	(0.227)	(0.273)	(0.337)
LagInnoProd	0.566***						
	(0.159)						
LagInnoProdRad		0.516***					
		(0.150)					
LagInnoProdInc			0.849***				
			(0.181)				
LagInnoProc				0.709***			
				(0.153)			
LagInnoProcRad					0.983***		
					(0.141)		
LagInnoProcInc						0.587***	

Table A3: Continued

	InnoProd	InnoProdRad	InnoProdInc	InnoProc	InnoProcRad	InnoProcInc	PatFile
						(0.189)	
LagPatFile							1.643***
							(0.200)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2200	2200	2200	2200	2200	2200	2200
sigma_u	1.733	1.647	1.551	1.611	1.321	1.783	1.317
rho	0.750	0.731	0.706	0.722	0.636	0.761	0.634
chi2(df)	163.713(31)	138.849(31)	156.759(31)	151.683(31)	145.242(31)	116.396(31)	122.182(31)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$