Reply to the comments made by referee 1 and 2 and the invited reader

First, I would like to thank the two referees (R1, R2) as well as the invited reader (IR) for their valuable comments. In the following, I reply to their remarks and suggestions. The comments allowed to improving the paper such that it now should come up to the standard required for a publication in the E-journal as an article.

Section 2: Data

We mentioned in the discussion paper that we corrected for *item-non response* by imputing missing values ("multiple imputation"). R1 suggests to discuss, firstly, why we use imputed values in case of missing values, and, secondly, to illustrate the effects of using a dataset that includes *imputed values* as compared to one that *does not contain imputations*.

We argue in the revised version of Section 2 why it is indispensable to correct for item non-response. Without imputation, we would have to drop from the dataset each firm (observation) as *soon as the value of one single variable is missing*. For example, we need about forty variables to identify and evaluate the innovation modes in Section 3. Without using imputed values, the number of observations available for this step of the analysis would be significantly lower. Therefore, the resulting pattern of innovation modes might become less robust. Moreover, we would be confronted with the same reduction of the number of observations in all other parts of the study (Section 4 to 6), as these build on the innovation modes previously identified.

However, in line with the second suggestion made by R1, we exemplify the *effects of not using imputed values* using as an example the results of the factor analysis (see subsection 3.2).

Section 3: Identification and interpretation of the innovation modes

Comparison with earlier work (subsection 3.4)

R1 suggests a *more detailed review of the extant literature* dealing with (firm-level) innovation modes, to allow a discussion of the *selection of the variables* included in the factor analysis, since this choice has an impact on the characteristics of the innovation modes that are identified (the latter point is also made by R2).

We may indicate that in *subsection 3.4* of the discussion paper we *referred to the available firm level studies* that seek to identify innovation modes by means of cluster analysis, and compared the results with those of the present analysis. We pointed to the fact (correctly mentioned by R1 and R2) that the results of such exercises depend, among other things, on the selection of the underlying variables (type and number of indicators). The review of the existing literature showed that previous studies mostly used *a specific mix of three up to seven categories of innovation indicators*. Because of the substantial differences among the various papers in terms of the number and the types of (categories of) indicators, a *one-to-one comparison* is not feasible. Such an exercise would require a very detailed discussion based on a large synoptic table of the characteristics of the various contributions. Such a detailed comparison is *not sensible* in the present context as we deal, in addition to the identification of innovation modes, with another three topics, which, in fact, are at the core of our contribution (Sections 4 to 6).

Moreover, we would like to point to the third paragraph of subsection 3.4 in the revised paper, where we mentioned *three basic conclusions one can draw from the comparison with other studies*. *Firstly*, several papers identified two of our five innovation modes: the science-based strategy and the investment-based strategy (cluster 1 and 2). *Secondly*, the most relevant difference between our study and the other ones lies in the fact that our analysis is the only one that found *two clusters for which an intensive use of IT is constituent*, the one process-oriented (cluster 3), the other product-oriented (cluster 5). This difference is due to the fact, that the other studies did not include any IT-related innovation indicators, which is quite surprising given the importance of IT at least since the 1990s.

The lack of IT-related indicators is thus a quite serious deficiency of previous work. *Thirdly*, our study is practically the only one that evaluates, whether the clusters identified by using purely statistical criteria are adequate from an independent, theory-based point of view ("economics of innovation").

We conclude that we may *largely* stick to the comparison with other papers as formulated in the discussion paper. We only clarify some points and draw the above-mentioned three conclusions.

Nevertheless, we added in subsection 3.4 of the revised version a final paragraph where we shortly discuss some work that applies a "*top-down approach*" for defining innovation strategies (in contrast to the "bottom-up" approach based on cluster analysis). This type of research uses some *a prioricriteria* to classify firms into a few categories of innovation modes (see, for example, Roud 2018).

Methodology (subsection 3.1)

Selection of the innovation indicators

With respect to a discussion of the *selection of the innovation indicators* underlying the factor analysis (and, as a consequence, the cluster analysis), which R1 and R2 ask for, we refer to the second paragraph of the revised subsection 3.1 (methodology). We mentioned that we use *fifteen* innovation *indicators that reflect the most important elements of the innovation process*. That is, (a) the *input* side and (b) the *output* side of the *generation* of product and process innovations as well as (c) the stage of the *implementation* of such innovations (introduction of product innovations on the market and of process innovations within the firm). Hence, there is a *coherent logic* leading the choice of the three types of indicators, which, as already mentioned, is not the case in previous research. Besides, *Table 1* of the discussion paper provides the *precise definition and measurement* of the fifteen innovation indicators used in our analysis. Hence, the definition and use of the variables should be *sufficiently precise* to satisfy a comment made by R1 and R2.¹

Step 1 of the procedure: factor and cluster analysis

We *slightly* adapt our original text on the *factor and the cluster analysis* in the second part of paragraph 2 of subsection 3.1 (of the discussion paper). In the revised paper, we provide a more precise description of the *method of non-hierarchical clustering* in a separate paragraph. We move the (slightly extended) explanation of the method from footnote 3 of the discussion paper to the main text. Additionally, we indicate that the application of the method rests, firstly, on a *principal component factor analysis* (using the SAS FACTOR procedure) and, secondly, on the SAS FASTCLUS procedure that provides an efficient method for identifying clusters in the case of a *large data set*.

Step 2 of the procedure: theory-based evaluation of the outcome of the cluster analysis

Step 2 of our methodology (see the third paragraph of subsection 3.1 of the discussion paper) *distinguishes our approach from that used in previous studies on this topic*. Our procedure is in line with the suggestions put forward in the statistical theory (as an example, we mentioned *Kaufmann and Pape 1996*), which emphasises the *need to evaluate the adequacy of the innovation modes based on theory-related variables not used in the clustering process* of step 1. To this end, we draw on the most important demand-side and supply-side determinants of a firm's innovation activity as postulated in the "economics of innovation". This procedure allows to assessing *whether we effectively may interpret* the clusters as specific innovation modes. We provided the *precise definition and the measurement of these variables* in Table 4 of the discussion paper.

To sum up

We assert that the presentation of the two-step methodology in subsection 3.1 of the discussion paper is clear and adequate. Step 1 determines, based on a non-hierarchical cluster analysis, a set of

¹ Moreover, we mentioned in Section 2 that the questionnaires underlying our work are available on the homepage of our institute. In this way, the reader gets the precise wording of the various questions on which our variables are based.

innovation clusters (a standard method), whereas *step 2* provides a theory-based evaluation of the clustering results that is necessary to assess whether the clusters identified in step 1 (by using a purely statistical method) may effectively be interpreted as specific innovation strategies. In Table 1 (innovation indicators) and Table 4 (variables used to evaluating the innovation modes), we provide very clearly the definition and measurement of these variables. Altogether, we hold that some clarifications and reformulations are sufficient to get subsection 3.1 in line with the suggestions of R1 and R2.

Results of the factor and the cluster analysis (subsection 3.2)

In subsection 3.2 (Tables 2 and 3), we presented the results of the factor and the cluster analysis. In our view, the optimal solution of the factor analysis is one with five factors. R1 asks why we choose five factors although this solution is not fully in line with the recommendations in OECD (2008) with respect to the selection of the number of factors. According to the OECD publication, three criteria should guide the choice: (a) the sum of the factors should explain at least 60% of the total variance; (b) each factor should explain at least 10% of the total variance; (c) the eigenvalues should be 1 or larger. The results of the factor analysis presented in Table 2 show that our five-factor solution is in line with (a), and the same is more or less true for (c) as the fifth eigenvalue amounts to 0.96. The results, however, are at odds with criterion (b), which, in our case, would suggest a 3-factor solution. In contrast to the OECD guidelines, we point to the fact that the statistical literature emphasises that one should not mechanically apply purely statistical criteria. This literature states that a factor solution should allow a convincing interpretation given the problem at hand. This is not the case for the 3factor solution implied by the OECD guidelines, as it forces, in some instances, clearly different aspects of innovation into one single factor. In contrast, each of the five factors we extracted represents a specific dimension of innovation activity that differs from that of the other factors (see F1 to F5 in Table 3). Hence, a five-factor solution is superior to one with a smaller number of factors. We discuss the problem of choosing the appropriate number of factors in a new paragraph of the revised subsection 3.2.

Moreover, R1 asks why we refer only to the variables with values larger than 0.4 for interpreting the rotated factor pattern (see the figures in bold in Table 2). We did so because for the interpretation of each factor only these variables are relevant (the correlations for the other innovation indicators, with very few exceptions, are below 0.2). We set the values larger than 0.4 in bold to provide the reader an immediate impression of the pattern of the results. Statistically, this does not matter as the subsequent cluster analysis makes use of the factor scores reflecting the *complete* factor matrix.

R1 suggests to providing some information on the *effect of using vs. not using imputed values*. We do so by taking the factor analysis as an example (see subsection 3.2 of the revised paper). The most important differences are the following: (a) if we renounce to using imputed values, the number of observations substantially decreases, with the effect that an analysis of the more complex problems we aim for in the Sections 4 to 6 would not be feasible; (b) independent of using or not using imputed values, a solution with five factors is optimal, although, in both cases, the purely statistical OECD criteria would suggest a 3-factor solution (the variance explained by the fourth and the fifth factor in both cases is below 10%); (c) the problem-oriented interpretation of the five factors is more convincing based on the dataset that includes imputed values. Nevertheless, the difference between the two approaches is not too large, as the interpretation of three of the five factors is very similar; (d) the subsequent cluster analysis is clearly superior if we use the dataset that includes imputed values. This version provides a set of innovation modes (five clusters) that corresponds to a higher extent to the insights provided by the "economics of innovation" than an analysis based on a dataset without imputations.

Section 4: Switches between innovation modes over time

We simplified the presentation of the results by dropping Table 6b of the original paper as it provides more or less the same information as that shown in Table 6a. Therefore, the old Table 6a becomes Table 6 in the revised version.

IR suggests to presenting an additional table showing the frequencies of the five strategies over time. However, we do not insert such a table, as it cannot not provide meaningful information on the development of the overall number of firms and the shares of each strategies for two reasons. Firstly, because the panel we have at our disposal is unbalanced and, secondly, as we only can consider firms that provided information for two successive waves of the survey and generated innovations in both periods.

R2 suggests that a transition matrix (conditional probabilities of switching from the original to one of the other innovation modes in the next period) would be a more effective way of describing the dynamics than our presentation in Table 6a in the discussion paper (Table 6 in the revised version). As our panel is unbalanced, a presentation as suggested by R2 is not feasible for the reasons we mentioned in the previous paragraph. We thus stick to the procedure applied in the discussion paper. That is, we use the absolute number of strategic switches (Table 5) to calculate for each strategy the *"ratio* between the *"inflows* of firms originally pursuing another strategy" and the *"outflows* of firms from the original to another strategy". Based on these ratios (Table 6 in the revised version), the reader gets *at a glance* the information required to assessing the *relative attractiveness of the five strategies*, which is the main objective of the *descriptive* analysis of the dynamics of innovation strategies.

Section 5: Intra-industry heterogeneity of innovation modes

We analysed the intra-industry heterogeneity of innovation modes – in analogy to Leiponen and Drejer (2007) – based on 4-digt industries containing at least *eight* or, alternatively, *ten* companies.

R1 suggests to calculate *additionally* the *share of industries without a dominating cluster* for industries containing *a larger number of observations* (more than ten), and to additionally insert these results in Table 8. We take up this proposal by choosing a *cut-off point of fifteen firms per industry* (implying that the number of 4-digit industries we could use decreases). As the heterogeneity of an industry tends to be larger the more firms it contains, we expected that the share of industries without a dominating cluster is higher than in the case of a cut-off point of ten companies per industries. As shown in the extended Table 8, this indeed is true (see row 1.C vs. 1.B and row 2.C vs. 2.B). In comparison with the cut-off point of ten companies, the share of industries without a dominating cluster increases from 75% to 82% if we use a cut-off point of fifteen firms; if we only consider industries with *clearly specified activities*, we get an increase from 75% to 80%. In sum, by raising the cut-off point from ten to fifteen companies per industry we do not get additional insights. We may add that we observe a similar increase if we use an even higher cut-off point (20 companies per industry).

Section 6: Innovation modes and firm performance

R1 suggests to specifying the productivity equation using *time lags* of the innovation mode variables. Moreover, he proposes to include an additional variable to control for "*the firm belongs to a group*". It indeed would be sensible to complement the model accordingly. However, we cannot adequately account for time lags, as our panel is unbalanced. We mention the point in the revised version, particularly as it is important with respect to the interpretation of the results of the productivity equation: *causality vs. correlation*. Moreover, the number of observations for which we have information on whether a firm belongs to a group is low, implying that the number of missing values is too large to allow a reliable imputation.²

² Our model controls for whether a firm is foreign-owned, which, to some extent, is related to the attribute "the firm belongs to a group".

R2 is not sure of how we measured the *dependent variable* used in the performance equations, i.e. *labour productivity*. In the discussion paper, we provided a precise definition in Table 9 but did not do so in Table 10 (estimation results). In the new version, we clearly mention in both tables and in the text that labour productivity throughout is measured by the "nominal value added per employee". Moreover, R2 suggests that, as the ultimate goal of the firm is to make *profits*, we should use (alternatively) as a dependent variable the "*the firms' market share*". However, we do not agree that "the firm's market share" is an appropriate indicator of "profits". Market shares do not necessarily correlate with profits as widely documented in the literature and the business press. Besides, we do not have information on more suitable indicators of profits such as, for example, the EBIT margin. In sum, we remain using a firm's labour productivity as dependent variable.

Furthermore, R2 argues that we should take account of the growing (macroeconomic) literature dealing with heterogeneity at different levels of aggregation. More specifically, referring to a few empirical studies, R2 suggests to including additional explanatory variables to account for *firm and industry heterogeneity*.³ *Largely* in line with the suggestions of R2, *we re-specify our model* with respect to the two categories of heterogeneities as far as it is sensible and feasible given the available data:

(a) Firm heterogeneity

To take into account the comments of R2, we include "firm age" ("the firm is less than ten years old, yes/no") as an additional variable representing firm heterogeneity. Moreover, R2 recommends, referring to Acemoglu at al. (2018), to take into account a measure of a firm's "innovation capacity". However, we hesitate to do so, as the three variables that, based on our dataset, are candidates for measuring a firm's "innovation capacity" ("a firm's technological/innovation potential in/around its fields of activity", "patenting yes/no", "patent intensity") strongly correlate with core variables underlying the "science-based innovation strategy". Moreover, the three measures quite generally correlate with the five strategy variables, as these are characterised not only by different configurations of innovation-related attributes but also by different levels of innovativeness (see subsection 3.3). For example, the three measures correlate positively with the "science-based innovation strategy" pursued by highly innovative firms and negatively with the "process/product-oriented strategy" pursued primarily by firms with low innovation intensity. Nevertheless, to take into account the suggestion of R2, we explore in the revised paper the role of the "technological/innovation potential in and around the firm's fields of activity", which is the variable most suited to capture a firm's innovation capacity. However, we do not find a statistically significant effect of this variable (see the estimates of model 5 in the revised Table 10). This result is not surprising in view of the "correlation problem" mentioned above. Therefore, we dropped this variable in the final equation (model 6).

(b) Industry heterogeneity

With respect to this type of heterogeneity, R2 points to the importance of two explanatory variables we did not take into account in the discussion paper, i.e. "competition" and "export opportunities". With respect to *competition*, R2 refers to the well-known contribution of *Aghion et al. (2005)*, which found an inverted U-shaped relationship between *competition and innovation*, meaning that an "intermediate degree of competition" is particularly favourable for generating innovations. However, as these researchers investigate the impact of competition on a firm's *innovativeness rather than productivity* (which is the dependent variable of our model), their findings do not provide an argument for including a "competition variable". However, we may argue that "strong competition" forces a firm to increase productivity because of a constant pressure to reduce production costs. Based on this reasoning, we inserted in our model a "competition variable" is a particular favourable environment for attaining a high level of productivity. We thus insert a dummy variable "the firm has more than five

³ In the *discussion paper*, we used "firm size" and "foreign ownership" to control for firm heterogeneities and captured industry heterogeneities by inserting 29 industry dummies. In the *revised* version, we use some additional controls as mentioned in the text above.

and less than ten principal competitors on the world market, yes/no". The estimates of model 5 and 6 indeed show a *positive and statistically significant influence* of this variable on labour productivity (see the revised Table 10). However, the *economic* relevance of the competition variable is low; moreover, it does not change the productivity effect of the five innovation strategies nor does it effectively improve the overall model fit (\mathbb{R}^2). Nevertheless, *we retain this variable in the final equation (Table 10, model 6)*, as it is theoretically well founded and statistical significant.

Referring to Aghion et al. (2018), R2 also suggests to using a measure of the "export opportunities" as a further variable to capture "industry heterogeneity". These researchers investigated, in the first place, the relationship between an export shock and innovativeness rather than the impact of exports on productivity. They only indirectly related exports to productivity, as they found that the impact of exports on innovation is particularly large for high productivity firms and particularly small for low productivity companies.⁴ Our database only allows to inserting a simple export variable, i.e. a firm's "export propensity" or, alternatively, its "export intensity", which obviously is not the best way to representing "export opportunities". The use of exports as a determinant of productivity is problematic as the direction of the causality between exports and productivity is not obvious. Wagner (2012), surveying a large number of empirical studies dealing with the relationship between international activities and productivity, shows that the causality runs in both directions. High productivity firms are present on export markets to a higher extent than low productivity companies are, primarily as foreign market entry is not costless. On the other hand, exporting entails learning effects that may raise productivity. Most studies found evidence for both effects, but the first one (productivity causing exports) is stronger. In spite of this "causality problem", we explore the role of exports in model 5 by inserting the variable "export propensity" (exporting yes/no). It turns out that it is positively associated with labour productivity (we get the same result by using "export intensity", i.e. the export to sales ratio). However, the two-way causality implies that, in a productivity equation, the export variable is endogenous, a problem that we cannot account for in our cross-section setting. We tried to reduce the problem of *endogeneity* by using for each firm the "average export propensity of the 3-digit industry to which the firm belongs", which is a method to correct for endogeneity proposed by Cassiman and Veugelers (2002). However, estimates with this alternative specification did not provide additional insights. The "size of foreign markets" would be a better measure of "export opportunities" as it is largely exogenous to a firm's activity. However, our dataset does not provide such information. In view of these problems, we drop the export variable in the final productivity equation (Table 10, model 6). A comparison of the results of model 6 with those of model 5 shows that the exclusion of the export variable does not change the effect of the five innovation strategies on labour productivity; moreover, it does hardly reduce the model fit.

IR suggests to optimising the productivity model by dropping the R&D variable (what we do in Table 10, model 6). Moreover, he suggests to use one single human capital variable (sum of the two human capital variables contained in our model) or to drop the human capital variable altogether. Estimates based on this alternative specification of human capital as well as estimates of models excluding human capital do not show any change of the productivity effect due to the variables representing the innovation strategies. Therefore, *we stick to the original specification of human capital input but dropped the R&D variable in the final equation (model 6).* More generally, IR recommends to documenting the results of the model estimates in more detail. We did so by presenting in the revised Table 10 estimates of *six models*, complemented by two equations serving to compare our results with those of previous research. The models 1 to 6 show the *different stages of our modelling*, i.e., from a very simple specification of the explanatory part (model 1: innovation strategies only) up to the final

⁴ Other studies to which R2 refers (*Bonfiglioli et al. 2018a and b*) formulate models that analyse, in the first instance, the effect of "export opportunities" on the change of the distribution of productivity across firms, *based on different intervening variables* such as, for example, the *size of innovation projects* (such information is missing in our dataset). They find that increasing export opportunities lead to a larger dispersion of the firms' productivity. However, these models are not helpful in the present context, as we do not aim at explaining the *change of the distribution* of productivity.

model 6 that contains the entire set of explanatory variables. In the discussion paper, we showed only three models (and a fourth one for comparing the results with those of previous work).

Besides, IR recommends to conducting a significance test for the joint effect of the five strategies vs. the joint effect of the industry dummies to allow an assessment of the two theoretical approaches analysed in this paper (strategic management view vs. technological regime approach). As the strategy variables and the industry variables are measured on different scales (metric vs. dummies), we cannot simply compare the sum of the coefficients of the two sets of variables as suggested by IR. Therefore, we proceeded as follows: We estimated the final model 6, firstly, excluding the variables that capture industry dummies. In the first case, we find that only two of the five strategy variables are statistically significant. In the second case, the industry dummies are jointly significant and we get a significantly higher R^2 than in the first one. These results confirm those of a comparison of the simple models 1 to 3 (Table 10); hence, industry effects still are larger than the strategy effects even if we account for factor inputs and heterogeneities at firm/industry level.

Moreover, IR presumes that productivity differences among industries may be path dependent (i.e., to some extent, historically given). Therefore, regressions referring to averages may not be the most appropriate way of dealing with the basic question at hand (strategic management vs. technological regime approach). Accordingly, he suggests to performing regressions *for firms with different productivity levels* in order to getting more reliable results with respect to the productivity effect of the five strategies compared to the effect due to industry affiliation. In addition, IR (tentatively) hypothesises that innovation strategies may contribute to productivity *only for high productivity firms*, but he does not present any arguments why this should be the case.

Following this suggestion, we estimate model 6 (Table 10) separately for five categories of firms characterised by different levels of productivity (quintiles). The results of these regressions (see the new subsection 6.4, Table 11) show that the firms of three of the quintiles are able to get a competitive advantage by choosing a specific innovation strategy. "Very low productivity firms" often choose an investment-based strategy, indicating that the adoption of innovations generated outside the firm is the dominant form of innovative activity. In contrast, the firms with an "intermediate productivity level" and those with a "very high productivity" choose IT-related strategies, which in the former case is product-oriented and in the latter process-oriented. Hence, the results based on the general approach conceal some differences among groups of firms with respect to the productivity effect of innovation strategies. However, since the success of the firms that belong to the three quintiles is based in each case on a different strategy and the strategy variables are insignificant for the other two quintiles (i.e. 40% of the firms), it is not particularly surprising that we find hardly any significant productivity effect of the strategy variables in model estimates based on the total sample. We conclude from the results based on the disaggregated approach that the optimal innovation strategy differs, to some extent, according to the firms' level of productivity (as presumed by IR). However, as these divergences are not very accentuated, the basic result of the dominance of industry effects remains valid, although with some qualifications. We shall take into account these results, which attenuate the dominance of the industry effects, in subsection 6.5 of the revised version, where we assess the estimation results for the relationship between innovation strategies and productivity.

Section 7: Future research

IR argues that it would be worthwhile to investigate the impact of our explanatory variables on the "sales share of innovative products" rather than using "labour productivity" as the latter variable is "a step more distant" from the innovation process. This would require, as IR correctly notes, a new factor and cluster analysis based on a set of innovation variables that *excludes the sales share of innovative products*. However, by dropping this variable, which represents the *implementation* of the outcomes of innovative activities on the market, a core element of innovation strategies would be lost. The innovation strategies resulting from such an alternative approach would be incomplete and perhaps

misleading. Nevertheless, it may be worth to explore such a model. We refer to this suggestion in Section 7 of the revised paper.

In addition, IR states that it would be interesting to investigate possible *determinants of the propensity to change the actual innovation strategy*. We may indicate that we mentioned this point in the last section of the discussion paper. In the revised paper, *we point to some candidates of variables* that one could use to explain the transition from one to another innovation strategy; see also the approach of Arvanitis and Seliger (2014) explaining the switch of firms from being an "imitator" to being an "innovator" (and vice versa). In any case, an analysis of the determinants of the change of innovation modes would be highly appreciated (as we mentioned in the discussion paper).

General points

R2 asks for clarifying the difference between the expressions "industry" and "branch". In the discussion paper, we used the two terms as synonyms. To not confusing the reader, we drop "branch" and use in the revised version throughout the expression "industry", independent on whether it refers to the 2-digit or the 4-digit NACE classification.

Moreover, R2 emphasises that the tables should be self-contained, particularly with respect to the variable definitions and the methods applied. In the revised version, the tables are adapted accordingly. Only in rare cases (i.e. if the size of a table does not allow to doing so) we refer to another table.

Finally, R1 asserts that the *paper may be too ambitious* as it deals with *four topics* that could be treated in separate papers. I do not agree with this view. Our analysis particularly aims at assessing the relative merits of the "strategic management concept" and the "technological regime approach" for understanding the firms' innovation behaviour. To this end, Section 5 (intra-industry distribution of innovation strategies) and Section 6 (innovation strategies vs. industry affiliation as variables to explain firm performance) are necessary. Section 3 aiming at the identification of innovation strategies is a precondition for performing the analyses presented in the Sections 5 and 6. Section 4, where we analyse the firms' switches from the current to another innovation strategy, is the only part not connected to the Sections 5 and 6. However, it is the first analysis of this topic based on a large panel data set, and it is a "natural follow-up" of the identification of innovation strategies in Section 3. As it is only a descriptive analysis, we doubt whether we could publish it as a separate paper. Given the deficiencies of the database (e.g. unbalanced panel, no information on potentially relevant explanatory variables), such an explanatory analysis has to be left to future research. In sum, it is sensible to treat the four topics in one single paper.

Literature

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W.R. Kerr (2018). Innovation, Reallocation, and Growth. American Economic Review 108(11): 3450-3491. <u>https://www.aeaweb.org/articles?id=10.1257/aer.20130470</u>

Aghion, P., A. Bergeaud, M. Lequien, and M.J. Melitz (2018). The Impact of Exports on Innovation: Theory and Evidence. *NBER Working Paper* 24600. National Bureau of Economic Research. Cambridge (MA). <u>https://www.nber.org/papers/w24600</u>

- Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005). Competition and Innovation: an Inverted-U Relationship. *Quarterly Journal of Economics* 120(2): 701-728. <u>https://dash.harvard.edu/handle/1/4481507</u>
- Arvanitis, S., and F. Seliger (2014). Imitation vs. Innovation: What Makes the Difference? KOF Working Paper 367. KOF Swiss Economic Institute, ETH Zurich. <u>https://doi.org/10.3929/ethz-a-010211535</u>

- Bonfiglioli, A., R. Crinò, and G. Gancia (2018a). Betting on Exports: Trade and Endogenous Heterogeneity. javascript:void(0)*The Economic Journal* 128(609): 612-651. https://doi.org/10.1111/ecoj.12408
- Bonfiglioli, A., R. Crinò, and G. Gancia (2018b). Trade, Finance, and Endogenous Firm Heterogeneity. *Journal of the European Economic Association* 2018 00(0): 1-52. https://doi.org/10.1093/jeea/jvx047
- Cassiman, B. and R. Veugelers (2002). R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium. *American Economic Review*, 92(4): 1169–1184. https://www.aeaweb.org/articles?id=10.1257/00028280260344704
- OECD (2008). Handbook on Constructing Composite Indicators. Methodology and User Guide. OECD: Paris.
- Roud, V. (2018). Understanding the Heterogeneity of Innovation Modes: Performance Effects, Barriers, and Demand for State Support. *Technological Forecasting and Technological Change* 133: 238-253. https://doi.org/10.1016/j.techfore.2018.04.025

https://doi.org/10.1016/j.techfore.2018.04.025

Wagner, J. (2012). International Trade and Firm Performance: a Survey of Empirical Studies since 2006. Review of World Economics 148(2): 235-267. <u>https://doi.org/10.1007/s10290-011-0116-8</u>