Article:

Corradini, Carlo and D'Ippolito, Beatrice orcid.org/0000-0003-0778-4373 (2022) Persistence and learning effects in design innovation : evidence from panel data. Research policy. 104452. ISSN 0048-7333

https://doi.org/10.1016/j.respol.2021.104452

Pre-proof version of the manuscript accepted on 01.12.2021, forthcoming in Research Policy.

Persistence and learning effects in design innovation: evidence from panel data

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Abstract
This paper explores persistence and learning effects in the aesthetic and symbolic dimensions of design innovation. By combining insights from innovation economics and design studies, we discuss design innovation as the result of firm-specific cumulative learning. We then conceptualise design and product innovation as complementary processes whose interplay may lead to learning effects across different dimensions of knowledge creation. We provide quantitative evidence for these insights applying dynamic probit and bivariate probit models to a longitudinal dataset of manufacturing firms based in Spain for the period 2007-2016. Our findings confirm the presence of persistence effects in design innovation, offering novel evidence in support of the view whereby design is an iterative process shaped by the knowledge generated through firms' previous engagement with design. In addition, the results contribute to our understanding of the role of design beyond its functional dimension, pointing to mutually reinforcing effects between aesthetic and symbolic design and product innovation.

Keywords: design, innovation, symbolic knowledge, product innovation, persistence, cumulative learning

JEL classification: O30, O31, O32, C33

Acknowledgements
We are extremely grateful to the editor Ammon Salter and the three reviewers, their thought-provoking comments allowed us to substantially improve the manuscript. The opinions expressed in this paper are those of the authors. The usual caveats apply.

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1. Introduction

Innovation scholars have long underlined the importance of looking beyond the traditional understanding of technological change and product innovation to fully comprehend the characteristics and dynamics of innovative firms (Barge-Gil et al., 2011; Filippetti, 2011; Stoneman, 2010). In particular, a significant strand of research has placed emphasis on how firms' design activities encompass not only the functional dimension of the innovation underpinning new products, but also the relevant aesthetic and symbolic components (D'Ippolito, 2014; Luchs and Swan, 2011; Luchs et al., 2016; Ravasi and Stigliani, 2012). There is established evidence in support of design as constituting an important contributor to both innovation and company performance (Perks et al., 2005; Roper et al., 2016; Rubera and Droge, 2013) as well as organisational strategies (Gemser and Leenders, 2011; Micheli et al., 2018). Similarly, scholars have discussed design orientation to signpost strategic approaches that rely on different types of design to deploy competitive advantage, including product design, packaging design, and graphic and interior design (Cantò et al., 2021; Moll et al., 2007; Venkatesh et al., 2012).

Against this background, and in contrast to the literature on other aspects of non-technological innovation, including organisational and service innovation (Camarero and Garrido María, 2008; Tether and Tajar, 2008), scholars have underlined that systematic quantitative evidence on design innovation remains limited (D'Ippolito, 2014; Filitz et al., 2015). A few studies have examined how investing in design may inform new product development and firms' innovative performance (Marsili and Salter, 2006; Montresor and Vezzani, 2020; Roper et al., 2016); however, this bulk of research has focused primarily on the functional dimension of design. As a result, evidence on the determinants of aesthetic or symbolic components of design innovation and the extent to which these may contribute to other innovative activities is scant.

In this paper, we merge perspectives from innovation economics and design studies to contribute to the literature on design innovation in two ways. First, we focus explicitly on determinants of design innovation that express novelty in the aesthetics and meanings of new products (Ravasi and Rindova, 2008; Verganti, 2003). This dimension of design rests on symbolic knowledge bases characterised by a set of informal capabilities (Asheim et al., 2007; Cappetta et al., 2006; Pina and Tether, 2016). As such, our analysis offers a complementary perspective to previous research that connects functional design to design engineering and formal research and development (R&D) activities (Dan et al., 2018; Marsili and Salter, 2006). We build on extant design management literature to argue that aesthetic and symbolic design innovation is a firm-specific endeavour, sitting on cumulative learning processes that unfold via trial-and-error feedback loops (Simon, 1969; Thomke, 1998). To test for the presence of such dynamics, we follow the approach defined by the literature on persistent innovation to capture endogenous learning effects, as previously identified in the case of product, process, and other types of innovation (Ganter and Hecker, 2013; Tavassoli and Karlsson, 2015). Accordingly, we focus on identifying true state dependence in design innovation, expressing the probability of innovating in one period as a function of the innovation output in the previous period, as opposed to spurious state dependence triggered by firm characteristics that have a degree of persistence themselves, such as size, R&D, or other unobserved effects.

Second, we explore whether learning effects generated by successful design innovation may spill over to product innovation and vice versa. A growing stream of research has focused on the role of complementary effects occurring between product, process, and organisational innovation to reveal how different innovation activities do not occur in isolation within firms; conversely, they may exert important systemic gains (Ballot et al., 2015; Battisti and Stoneman, 2010). Here, we consider the hypothesis of mutually reinforcing effects between design and product innovation, shedding light on the learning opportunities that may occur across different knowledge bases (Asheim et al., 2007; Walsh, 1996). By exploring these effects within a unified framework, we address recent calls for a deeper understanding of the interaction between symbolic design and product innovation (Filitz et al., 2015; Utterback et al., 2006; Verganti, 2008).

To test these hypotheses, we draw on a longitudinal dataset of over 2,000 Spanish manufacturing companies covering the period 2007-2016. We first employ a dynamic probit model accounting for unobserved heterogeneity and the initial conditions problem to offer evidence of true state dependence in design innovation (Wooldridge, 2005). Then, we apply a dynamic random-effects bivariate probit framework and System GMM regression to explore cross-effects across design and product innovation. Our findings extend previous evidence on persistent innovation to indicate the importance of firm-specific cumulative learning for aesthetic and symbolic design and provide novel empirical evidence on significant synergies between design and product innovation, integrating extant research on this relationship.

The remainder of the paper is structured as follows. In Section 2, we review the literature on design innovation to define the hypotheses of this study. In Section 3, we present data and variables employed in the analysis along with the estimation approach for the analysis. In Section 4, the results of the empirical analysis are reported. We conclude with implications of the study and opportunities for further research in Section 5.

2. Literature review and hypotheses

2.1 Defining design innovation

In the literature, design innovation has been conceptualised from a broad range of perspectives. Following a holistic approach, design can be defined as constituting firms' capability to generate and improve new ideas by drawing on feedback that they receive not only with regard to the product, but also the processes and organisational context that accommodate such innovation (Petroski, 1985; Vincenti, 1990; Walsh et al., 1992). In this sense, design processes embed the cumulative development of an initial creative act, which is further elaborated within reflective and meaning-making practices (Ardayfio, 2000). This creative act can find expression in either functional or aesthetic features of a product (Filippetti and D'Ippolito, 2017; Ravasi and Rindova, 2008).

The functional dimension of design is primarily centred on engineering know-how and it often connects to the technological elements of a product (Candi, 2006). As such, this dimension pertains to what a product is supposed to do and what utility it has (Bloch, 2011). It is mostly within this perspective that design has been explored as an input to new product development in innovation studies. R&D expenditure in industrial design has been shown to contribute to firms' innovative performance and productivity (Cereda et al., 2005; Marsili and Salter, 2006). Similarly, collaborating with designers for production engineering or prototype development has been associated with increased sales of new products (Roper et al., 2016).

Design activities are not solely confined to the engineering and functional components of new products (Eisenman, 2013). Scholars have increasingly drawn attention to the value that derives from the aesthetic component of design, expressed via visible attributes such as colour, shape, or texture (Candi et al., 2017; Seth et al., 2009). It has also been argued that the aesthetic dimension of design may go beyond the form of a product and encompass its emotional value that firms can purposefully target at given audiences (Tether, 2005; Utterback et al., 2006; Verganti, 2009). Following a similar conceptualisation, scholars often refer to symbolic design to identify instances when the product resonates with consumers' self-image, personality, and identity (Seva and Helander, 2009). Whilst less tangible, the contribution of symbolic design in conveying 'meaning' through new products is increasingly relevant for generating users' value (Verganti, 2017). Meanings are embedded in the emotion and the symbolic values of the product and aim at satisfying the emotional and sociocultural needs of the customer (Margolin and Buchanan, 1995). As pointed out by Dell'Era and Verganti (2007), the Apple iMac launched in 1998 transformed a computer into a piece of furniture, introducing innovative product signs such as daring colours and translucent plastic: "a breakthrough innovation from an aesthetical point of view compared with the common archetype of personal computer" (2007:581). Although the boundaries between aesthetic and symbolic design are more clear-cut in the fields of consumer psychology and design ergonomics, they are often considered as one by innovation scholars (Alcaide-Marzal and Tortajada-Esparza, 2007; Eisenman, 2013; Livesey and Moultrie, 2008). Drawing on the latter approach, in the remaining of the manuscript we discuss the aesthetic and symbolic dimensions of design activities together.

In contrast to the inherent linkages between functional design, R&D engineering, and product innovation, the aesthetic and symbolic dimensions of design activities tend to reside in a different set of capabilities rooted in knowledge of forms, language, and meanings (Verganti, 2008). This knowledge is transmitted through signs, symbols, images, narratives, or sounds, and is especially relevant to creative functions within firms (Pina and Tether, 2016). In this sense, a firm's symbolic knowledge base is characterised by a strong tacit component and firm-specific know-how, which depends on interpretation rather than information processing (Asheim et al., 2007). As a result, design innovation rests on integrating "knowledge about different socio-cultural contexts proposing new aesthetical solutions that can become paradigmatic" (Dell'Era and Verganti, 2009:3).

This process is testimony of how the development of a new design leads to the formation of distinctive design innovation capabilities through a knowledge-based process of cumulative learning. This design-based learning seems to also inform the wider innovation approach: due to the creative knowledge basis underpinning design, firms learn different elements of a product at each prototype iteration, leading design to pervade across other organisational functions (Borja de Mozota and Kim, 2009; D'Ippolito et al., 2014). It is to these aspects of learning and potential spillovers across innovation types that we now turn our attention.

2.2 Learning and persistence effects in design innovation

A long tradition of studies has emphasised the role of learning and knowledge as fundamental drivers of innovation dynamics. This body of knowledge can be traced back to two different yet related perspectives (Lundvall and Johnson, 1994; Nooteboom, 1999). A first perspective focuses on R&D activities as the input to new knowledge creation and a measure of learning processes within firms (Balconi et al., 2010; Raymond et al., 2010). The relationship between firms' R&D expenditure and their innovations is not confined to scientific research. It also comprises efforts in applied research directed at exploring new ideas, but it may equally be triggered by practice in the development of new products or from users' needs (Jensen et al., 2007). Innovation resulting from R&D certainly relies on a significant amount of tacit knowledge; however, the underlying learning processes tend to be defined by the presence of codified or codifiable knowledge. Furthermore, continuity in R&D expenditure may generate a stable stream of innovation over time (Duguet and Monjon, 2004; Geroski et al., 1997). This is reinforced by the presence of sunk costs in R&D, which provide incentives to carry on with R&D activities even if they are experiencing failure (Sutton, 1991).

Scholars have argued that design relates to this type of R&D to the extent that design captures the trial-and-error efforts embedded in the development of the prototype. Arguably, design sits between the 'research' and 'development' of new products (Barge-Gil and López, 2014). How the relationship between the two unfolds may depend on which aspect of design is considered. Various studies found a positive relationship between R&D expenditure and the functional dimensions of design (Cereda et al., 2005; Marsili and Salter, 2006). Conversely, aesthetic or symbolic innovation is markedly rooted in tacit knowledge; as such, it relies on less formalised knowledge sources as opposed to scientific knowledge or principles. These dimensions of design do not require the significant fixed costs associated with technological invention and firms focusing on these design activities seldom engage simultaneously in R&D (Pina and Tether, 2016).

A second perspective has placed at the centre of the analysis the specific dynamics of new knowledge creation (Nelson and Winter, 1982). According to this strand of research, innovation may derive from the presence of dynamic increasing returns in innovation defined by 'learning by doing' and 'learning to learn' effects (Klevorick et al., 1995; Rosenberg, 1976). This hypothesis refers to a common concept in evolutionary economics whereby learning and new knowledge capabilities emerge from innovation activity previously undertaken within the company. This is reflected in persistence effects, where the innovation output in a given period of time becomes an input for future innovation activities (Dosi, 1988; Nelson and Winter, 1982). Building on this, an empirical strand of research has focused on disentangling learning effects resulting from the output of previous innovation – reflecting true state dependence – from other firm-specific routines and characteristics conducive to innovation which also have a degree of stability – reflecting spurious state dependence – to offer evidence of dynamic increasing returns and cumulative learning effects for product and other types of innovation (Ganter and Hecker, 2013; Tavassoli and Karlsson, 2015).

This latter perspective can be associated with the insights offered by the literature on aesthetic and symbolic design innovation, mostly qualitative in nature, which suggests that sustained engagement in design relies on previous designs and concepts (D'Ippolito et al., 2014). These very dimensions of design, rooted in symbols and meanings, are firm-specific, sit on learning processes that unfold via trial-and-error feedback loops, and become hard to transfer across companies (Martin, 2009). Similarly, design-driven innovation leads to novelty of meaning and design language through a knowledge-based process that is defined within firms (Verganti, 2008). These elements indicate how cumulative learning reflected in persistence effects is inherent to design processes, as the output of a given design becomes input for the next innovative effort. Based on the above, we hypothesise the following:

Hypothesis 1. Design innovation is defined by true state dependence.

2.3 Learning across design and product innovation

Learning effects from design innovation are not confined exclusively to design activities, but can spill over onto other forms of innovation, in particular product innovation. Previous research has underlined the importance of complex innovation strategies, whereby various types of innovation activities are combined and connected allowing to achieve synergistic gains (Battisti and Stoneman, 2010; Filippetti, 2011). Most attention has been devoted to the analysis of competitive advantages deriving from linkages between product, process, or organisational types of innovation (Ballot et al., 2015; Evangelista and Vezzani, 2010; Le Bas and Poussing, 2014). Yet, potential complementarities exist not only at the crossover among innovation functions, but also at the intersection of different knowledge bases. Scholars have drawn attention to the positive effects arising when heterogeneous knowledge domains are coupled (Fleming, 2001; Schoenmakers and Duysters, 2010). The integration of distant knowledge bases reflects a process of explorative search that widens innovative capabilities with the aim of effectively absorbing and integrating a broader set of novel combinatorial opportunities, eventually leading to the development of more radical innovations (Corradini and De Propris, 2017; Fleming, 2001; Fleming and Sorenson, 2001).

Accordingly, it is possible to argue that there may be mutually reinforcing effects when new knowledge is generated through product and design innovation. The question as to whether design innovation as a major source of creativity can generate further innovation rests on the premise that a 'coupling' process between the image or meaning of a new product and its functions does occur (Walsh, 1996:514). Recent research has drawn attention to the presence of knowledge spillovers among analytical and symbolic knowledge bases, whose recombination may generate further advantages for innovation (Asheim et al., 2011; Pina and Tether, 2016; Tödtling and Grillitsch, 2015). Indeed, previous studies underline the crossover of know-how between design and production functions and the presence of competitive advantages when both aspects are developed (D'Ippolito et al., 2014; Rubera and Droge, 2013; Swan et al., 2005). A new product may lead to new product forms or enable the industrialisation of product designs previously considered impracticable. Product innovation can influence new product design also when a new technology is introduced; extending the functionality of new products may generate novel symbolic meanings and, in turn, trigger complementary design activities (Eisenman, 2013).

Similar dynamics may also apply in the opposite direction. Design can play a pivotal catalyst function within the organisational context because of its ability to bridge across different units, shaping their evolution and decision-making processes over time (Perks, 2007). Recent findings indicate how design is interwoven with other aspects of firms' innovation processes: the more central the role of design within a firm, the higher the likelihood that the firm innovates (Montresor and Vezzani, 2020). As firms develop new design knowledge, the intangible nature of design connects with the set of knowledge and resources that firms will have to mobilise across the various organisational units (Micheli et al., 2018). The creation of new meanings through design-driven innovation may similarly generate opportunities for the development of new products (Verganti, 2017). In this way, learning from previous successful design may shape product innovation through feedback and 'learning to learn' effects. In other words, generating new design know-how not only helps firms becoming better at 'doing design', but also expands their expertise to include new domains (Yoo and Kim, 2015).

In line with the above arguments, we put forward the following hypothesis:

Hypothesis 2. There are mutually reinforcing effects between design and product innovation.

3. Data and methods

3.1 Data

In order to test our hypotheses, we make use of a panel of manufacturing firms over the period 2007-2016 included. Data for the empirical analysis come from ten consecutive rounds of the Spanish survey on business strategies ESEE (Encuesta Sobre Estrategias Empresariales)[1], which covers the population of Spanish manufacturing firms with 200 or more employees and a random stratified sample for all companies between 10 to 200 employees. The empirical analysis presented is based on a sample of 2,497 firms for which complete data were available over the period considered. Focusing on Spanish data provides an interesting context for our research. Spain accounts for a significant share of manufacturing in Europe and whilst business R&D expenditure is moderate, turnover in design activities as well as trademark registrations are above the EU average (BEDA, 2018; EUIPO, 2021). At the same time, the questions in the ESEE are based on the Oslo manual and resemble those available in the widely used Community Innovation Survey (CIS), but provide the advantage of being available for every year, instead of the three-year periods in the CIS.

3.2 Variables

To capture design innovation, we use a specific question within the ESEE survey that asks companies to indicate, for every year from 2007, whether they introduced innovations of

[1] Available at: https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp.

commercialisation that are related to significant modifications in the design or packaging[2] of their products (Section E, question 10.1).[3] Accordingly, DESIGN INNOVATION is defined as a binary variable that takes the value of 1 if the company introduced innovations that reflect significant novelty in product design and 0 otherwise. This measure is clearly centred on novel forms and appearance of products, allowing to disentangle aesthetic and symbolic aspects of design activities from the functional dimension of design, which is associated with engineering-driven activities and often considered under the 'product innovation' umbrella (Dan et al., 2018; Marsili and Salter, 2006). This definition provides a general measure of design and, at the same time, guarantees that design is associated with a specific new innovation output. The focus on design output is consistent with previous studies on innovation persistence; also, it allows to overcome limitations in capturing expenditure on design activities, which are often inconsistent and un- or under-recorded (Tether, 2005).

To capture product innovation, we follow previous studies on persistent innovation (Ganter and Hecker, 2013; Tavassoli and Karlsson, 2015) and define PRODUCT INNOVATION as a dichotomous variable which is equal to 1 if companies introduced a product innovation new to the market, and 0 otherwise. This is based on a question in the ESEE survey (Section E, question 7.A) that asks whether companies have obtained product innovation reflecting completely new products or with modifications so important as to make them different from what was produced before[4].

[2] This is consistent with packaging design being considered an important aspect of product design (Cantò et al., 2021; Venkatesh et al., 2012).
[3] This question is asked separately from others on product innovation allowing to assess the two types of innovations separately. In its original formulation, the question reads as follows: "Indique si su empresa introdujo innovaciones de comercialización referentes a modificaciones significativas en el diseño o el envasado de sus productos".
[4] In its original formulation, the question reads as follows: "Indique si la empresa ha obtenido innovaciones de producto (productos completamente nuevos o con modificaciones tan importantes que los hacen diferentes de los que venía produciendo con anterioridad)".

A set of control variables is then added to our model. We control for R&D intensity, measured as the total amount of firms' R&D expenditure over firm turnover (R&D INTENSITY). We also include the variable GRADUATES SHARE, which reflects the percentage of engineers and graduate employees in the firm. Previous literature has underlined the importance of cooperation in innovative activities (Tether et al., 2002; Tojeiro-Rivero and Moreno, 2019). We account for this including a dichotomous variable (COOPERATION) being equal to 1 if the firm was engaged in active collaboration for innovation, and 0 otherwise. The variable EXPORTS, calculated as the amount of exports by the firm, is added to capture the importance of operating in international markets which are usually associated with more innovative companies (Aghion et al., 2018). We also include controls reflecting the age of the firm and firm size, measured as the total number of employees. To account for the differences in opportunity conditions available to firms, which describe the pace of the innovation advance in the environment where firms operate and the different rate of innovation across industries, we insert a set of sectoral dummies representing 20 manufacturing industries from the NACE classification[5]. Finally, time dummy variables are also included.

3.3 Estimation methodology

We analyse persistence in design innovation following the widely established approach based on a dynamic probit model whereby the likelihood for firm *i* to introduce new design output in time *t* (y_{it}) is defined as a latent function of design innovation in the previous period (y_{it-1}), controlling for observable characteristics as well as unobserved individual heterogeneity and the initial

[5] For the list of industries, please see Table 4.

conditions problem to capture true state dependence (Ganter and Hecker, 2013; Peters, 2009; Tavassoli and Karlsson, 2015). In this framework, the output of previous design innovation becomes input for the next innovative effort reflecting a process of cumulative learning, allowing us to reflect the tangled relationship between design process and outcome (Tether, 2005).

Following this stream of research, we use the conditional maximum likelihood estimator suggested by Wooldridge (2005), where the distribution of the unobserved effects is conditional on the initial value and a set of exogenous variables. Estimation of a standard probit model would require making a strong assumption of independence with respect to the relationship between the initial observation y_{i0} and the random intercept c_i. Yet, because the start of our sample does not correspond to the start of innovative activities of firms, estimates could be affected by an initial conditions problem that arises when the innovative behaviour of firms in the initial period y_{i0} is also influenced by unobserved time-invariant firm heterogeneity that affects current innovation activities. If the initial conditions are correlated with c_i, the estimator will be inconsistent, providing biased results that would lead to an overestimation of state dependence. The approach suggested by Wooldridge (2005) allows to estimate the effect of true state dependence, accounting for the initial conditions problem (Heckman, 1981), specifying the density of (y_{i0} , … ,y_{iT}) conditional on (y_{i0}, X_i). Hence, we specify the unobserved firm heterogeneity as a function of the initial values of the innovation dummy and a set of time-averaged covariates X_i. As suggested by Rabe-Hesketh and Skrondal (2013), we also include initial values for all regressors to avoid any further bias[6]. As Wooldridge (2005) explains, this

[6] Compared to previous studies on persistent innovation based on the CIS, the longer time dimension in our data provides better finite sample performance for the Wooldridge method (Akay, 2009).

requires a balanced sample reducing our dataset to 839 firms[7]. At the same time, this approach provides specific advantages with respect to potential sample selection and attrition issues, as these are accounted for as a function of the initial conditions y_{i0} (Wooldridge, 2005:44).

To explore the presence of a potential interdependent relationship between design and product innovation, we apply dynamic bivariate probit regressions to jointly estimate the equations for product and design innovations, with the aim of modelling the outcome of the former as increasing the likelihood for the latter and vice versa, under the assumption of correlated errors amongst the two processes. In particular, we follow the approach by Elliott et al. (2019) and apply the Wooldridge procedure for dealing with the initial conditions issue and unobserved heterogeneity to the bivariate probit framework[8]. For robustness, we also explore these dynamics using two separate equations, one for DESIGN INNOVATION and one for PRODUCT INNOVATION, in which instruments are used to remove potential endogeneity in the estimation. To do so, we apply the System[9] Generalised Method of Moments (Sys-GMM) two-step estimator (Blundell and Bond, 1998) with finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005). Given the binary nature of the dependent variables, these regressions are estimated as linear probability models. This allows us to control for any potential dynamic effect in the model in line with the hypothesis of persistent innovation, whilst providing consistent estimates in the presence of reverse causality.

[7] For robustness, we also estimated a dynamic probit model extending the Wooldridge approach to the case of unbalanced panels following the recent contribution by Albarran et al. (2019). Estimates were obtained using the Stata software XTPROBITUNBAL by Albarran et al. (2020). Results are consistent and are available upon request.
[8] This is estimated using the Stata software cmp by Roodman (2011) as a special case of conditional recursive mixed-process.
[9] This is preferred to the difference GMM estimator, which may produce weak instruments in the presence of highly persistent variables (Blundell and Bond, 2000).

4. Results

4.1. Descriptive statistics

We start our analysis by exploring key descriptive statistics for the variables in the dataset, which are reported in Table 1. We observe that around 17% of sampled firms report having introduced a new product, which is slightly higher (by ~4%) than the results obtained by manufacturing companies in the CIS across the period considered. A smaller percentage of companies reports the introduction of design innovations, with DESIGN INNOVATION around 11%.

Insert Table 1 about here

Insert Table 2 about here

Average values for product and design innovation suggest that the two are not necessarily connected. Indeed, when we look at correlation coefficients reported in Table 2, we observe how product and design innovation show a moderate correlation (0.32). Correlations with other variables similarly suggest differences across the two activities. The correlation with R&D intensity is markedly higher in the case of PRODUCT INNOVATION whilst it is quite low with respect to DESIGN INNOVATION, suggesting that undertaking aesthetic or symbolic design is not strongly dependent upon formal research activities (Pina and Tether, 2016; Walsh, 1996). We also observe how the presence of engineers and graduate employees, captured by GRADUATES SHARE, is more strongly associated with PRODUCT INNOVATION than DESIGN

INNOVATION. The same applies to COOPERATION and EXPORTS. Overall, correlations values are moderate, suggesting that multicollinearity is not of major concern in the analysis.

To further explore the differences between product and design innovation in our sample, we report in Figure 1 the percentage of companies introducing only design or only product innovation, both at the same time or neither. Whilst the percentage of firms introducing only design innovation is relatively steady across time, in the 5-6% range, we observe a slight decrease from 13% to 9% in firms that introduce product innovation only, most likely as a consequence of the financial crisis that Spain experienced at some point within the observed timeframe. At the same time, this is partly counterbalanced by firms within the sample introducing both types of innovation in the last three years, from 5% to a peak of almost 7% in 2015. This does not imply that the same firms are persistently engaged in innovation. A first look at the changes and persistence in innovation within the sample is offered by the transition probability matrices, showing the percentage of firms changing from one innovation state to another. These are reported for periods of 1 year, 5 years, and 10 years in Table 3. Similarly to what Cefis and Orsenigo (2001) found about persistence in patenting activities, the probability of remaining persistent innovators decreases rapidly across time. For design innovation, 60% of firms in the sample introducing design innovations remain in this state after 1 year; yet, only around 38% remain design active after 10 years. This is particularly the case for firms engaging in both product and design innovation, as 52% still introducing both innovations in the following year reduce to 18% after 10 years.

Insert Figure 1 about here

Insert Table 3 about here

Finally, we also observe differences in the propensity to introduce new products and design innovation across sectors, which are reported in Table 4. While *Furniture, Leather and footwear* as well as *Textile and clothing* sectors are quite similar in terms of the two innovation metrics, *Machinery, Computer products, electronics and optical* as well as *Vehicles and accessories* have a much higher introduction of products rather than design innovations. We also note how sectors in *Food and Beverages* have relatively higher values for DESIGN INNOVATION, which may be due to this variable capturing design innovation beyond aesthetic novelty and including packaging[10].

Insert Table 4 about here

4.2 Regression analysis

We start exploring the presence of persistence effects in design innovation looking at dynamic probit regressions, whose results are reported in Table 5. In column 1, we have the coefficients for a standard panel probit regression, which is based on the full, unbalanced sample of firms. We find a significant effect for the lagged term of design innovation, although this may be spurious and resulting from differences in initial conditions or other unobserved firm-specific

[10] To control for potential bias due to overrepresentation of packaging innovation activities in these industries, we have run our analysis by removing sectors 1-3 in Table 2. The results reported are robust to this approach.

factors. Most of the control variables are also significant, including the presence of product innovation, exporting, cooperation as well as size of the firm. In contrast, we do not find a significant effect for R&D intensity. When we move to coefficients for dynamic probit models in column 2, we confirm a positive and significant effect for previous design activity. Controlling for initial conditions and unobserved heterogeneity, this provides evidence of true state dependence in design innovation, suggesting the presence of cumulative learning effects in line with Hypothesis 1. As in the previous model, we observe that R&D intensity is not statistically significant in this model specification, suggesting that aesthetic and symbolic design innovation may be linked mostly to cumulative learning effects in design activities rather than formal R&D[11]. In contrast to the link between the functional dimension of design and R&D identified in previous studies (Marsili and Salter, 2006; Roper et al., 2016), our results provide evidence that the stronger component of symbolic knowledge associated with design activities is likely to rely more on problem solving and experience compared to formal research expenditure (Pina and Tether, 2016; Verganti, 2008).

Insert Table 5 about here

To explore the presence of simultaneous cross-effects between design and product innovation, we now move to the results of the dynamic bivariate probit model where DESIGN INNOVATION and PRODUCT INNOVATION are jointly estimated. In Table 6, we present results based on the full sample in column 1, while in column 2 we have estimates accounting for

[11] The within-means coefficient for R&D INTENSITY is equally not statistically significant, suggesting the long-term impact of R&D on design innovation is also unclear.

initial conditions and unobserved heterogeneity. Results are consistent; however, as in the models reported in Table 5, we note that the estimates without accounting for initial conditions and the unobserved heterogeneity tend to overestimate the impact of persistence effects. Overall, we find a positive and significant impact of design on product innovation, as identified in recent studies (Montresor and Vezzani, 2020; Roper et al., 2016). Furthermore, our results point to significant evidence of product innovation on the introduction of design innovation. This reflects the broader literature on complex innovation strategies in innovation (Battisti and Stoneman, 2010), extending the arguments of recombinant knowledge to the case of design and product innovation. The latent variable reflecting the impact of dynamic effects is also significant for both types of innovation. While this confirms previous studies on true state dependence in product innovation (Ganter and Hecker, 2013; Tavassoli and Karlsson, 2015), our findings suggest that this aspect is important also for design innovation.

To better understand the cross-effects between design and product innovation, we report predicted probabilities for DESIGN INNOVATION and PRODUCT INNOVATION in Figure 2, with other control variables at mean values. For companies that did not introduce design innovations in the previous period, we still observe a positive effect of PRODUCT INNOVATION on DESIGN INNOVATION. In line with H1, the likelihood of design innovation is much higher for firms that introduced new design before. Again, such effect further increases when product innovation is also introduced. As shown by confidence intervals reported in Figure 2, differences in these effects are statistically significant. Similar effects occur for product innovation. The interdependence between design and product innovation is also confirmed by the correlation (ρ) in the residuals of the two equations, suggesting that these activities are positively connected by some unobserved factors.

With respect to the control variables, as expected from previous literature, R&D intensity is a significant determinant of product innovation. Conversely, in line with the results from dynamic probit models (Table 5), the coefficient for R&D INTENSITY is not significant in the case of DESIGN INNOVATION. The difference in the role of R&D in the joint estimation of product and design innovation reinforces the view that these activities may rely on different types of knowledge bases. While product innovation benefits from both persistence effects and formal R&D activities, design innovation relies specifically on informal learning processes, hereby captured by persistence effects, rooted in in tacit knowledge of forms and meanings (Asheim et al., 2011; Pina and Tether, 2016; Verganti, 2008; Walsh, 1996). It is noteworthy to point out that our measure of design innovation captures aesthetic and symbolic features of new products. This complements rather than contradicts previous studies that found a positive effect between design engineering, which is more strictly associated with analytical and synthetic knowledge, and formal R&D activities (Dan et al., 2018; Marsili and Salter, 2006). As in the dynamic probit approach, we find a significant and positive effect for cooperation activities, extending this finding also to design innovation. Although we do not capture the extent of collaboration on the introduction of new design, this provides statistical validity to qualitative studies pointing to the role open structures may play in design activities (D'Ippolito et al., 2014; Eisenman, 2013; Walsh, 1996).

Insert Table 6 about here

Insert Figure 2 about here

Finally, as robustness check, we apply system-GMM regressions to explore dynamic effects whilst controlling for reverse causality from one type of innovation to the other. Results are reported in Table 7. In both models, the Hansen tests for over-identifying restrictions are not significant, confirming the validity of the instruments in our estimations. Similarly, Arellano-Bond tests for serial correlation are as expected, with negative and not significant third-order serial correlations[12]. While the coefficient for cooperation activities is no longer significant in neither type of innovation, main results are consistent overall. Again, we observe a significant impact of design on product innovation for the GMM estimates on the left of Table 7. At the same time, product innovation is a significant determinant of design, as shown in the model on the right, in Table 6. In both cases, we still find evidence of persistence dynamics. Similarly, R&D intensity is found to be significant for product innovation, but not for design.

Insert Table 7 about here

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5. Discussion and conclusions

In this paper, we explored how the aesthetic or symbolic dimensions of design innovation can trigger learning that not only informs subsequent designs but also shapes the wider set of firms' innovative activities. By merging perspectives from innovation economics and design studies, the research offers novel insights on how this learning is situated within firms' innovation strategy and organisation (Micheli et al., 2018; Verganti, 2009). First, we confirm the presence

[12] Accordingly, lags are used as instruments only from lag 3 onwards.

of true state dependence in design innovation by applying a dynamic probit model to a longitudinal panel of Spanish manufacturing firms for the period 2007-2016. Thus, our analysis extends to the case of design previous findings on persistence effects related to other types of innovation (Ganter and Hecker, 2013; Tavassoli and Karlsson, 2015). The results presented offer quantitative evidence reinforcing the view that design innovation constitutes an iterative process of problem-solving activities that rests on firm-specific cumulated knowledge (D'Ippolito, 2014; Pina and Tether, 2016; Verganti, 2008). Furthermore, we argue that learning effects generated by new knowledge that originates from design innovation are not confined solely to further design activities but may also affect other forms of innovation within firms. We test this by applying dynamic bivariate probit regression to estimate a system of equations where both product and design innovation are treated as connected by mutually reinforcing effects and are jointly estimated. Our findings confirm that the two processes are intertwined within firms' innovative activities, extending previous research on systemic gains from complex innovation strategies (Battisti and Stoneman, 2010; Filippetti, 2011; Le Bas and Poussing, 2014). Results are shown to be robust to GMM estimation.

5.1 Theoretical implications

The findings illustrated in Section 4 shed light on the learning dynamics that underpin the aesthetic and symbolic dimensions of design innovation as well as their mutually reinforcing influence on product innovation, complementing previous quantitative studies that highlight the functional dimension of design within firms' innovative activities (Cereda et al., 2005; Marsili and Salter, 2006; Roper et al., 2016). Despite the less formalised nature, we contend that the aesthetic and symbolic dimensions of design play a similarly meaningful role in terms of triggering further innovation; in particular, the findings make one step further by evidencing that design shapes not only subsequent designs but also product innovation. Accordingly, our research contributes the innovation literature through two main building blocks.

First, we confirm that design is defined by true state dependence, suggesting that previous innovation can spur further innovation through learning effects. This learning can relate to the core activities of design, such as specification, concept design, detail design, and manufacture (Pugh, 1986, 1991). Learning can also substantiate the set of interdependent tasks that can characterise more complex design projects (Smith and Eppinger, 1997). In either case, design innovation can be seen as the result of *firm-specific* learning, which originates from prior accumulated design knowledge. Thus, our results provide statistical validity to previous insights from case studies and qualitative research on the iterative nature of design and design innovation as a knowledge-based process (Ravasi and Rindova, 2008; Verganti, 2008). A further implication of this key finding is that trial-and-error learning is present not only when developing a prototype (i.e., the functional dimension of design), but also with regard to the aesthetic or symbolic dimensions of a new design (Pina and Tether, 2016).

Second, we extend this literature by highlighting how design interrelates to other types of innovation. We confirm previous studies arguing for a role of design as shaping firms' decisions related to new product development (Montresor and Vezzani, 2020; Roper et al., 2016). At the same time, the success of design innovation depends on the extent to which firms successfully learn and build upon their product innovations. By pinpointing how learning effects from design and product innovation may lead to mutually reinforcing effects, this manuscript connects with extant research that draws attention to the advantages of complex innovation strategies, whereby firms engage simultaneously in different types of innovation activities (Battisti and Stoneman, 2010; Le Bas and Poussing, 2014). While this strand of the literature has primarily focused on different innovation functions without considering potential differences in the underlying knowledge, our results emphasise how complementarities and learning occurring between design and product innovation not only bridge different innovation activities, but may also act as catalysts across different knowledge bases. In line with previous studies underscoring the presence of a competitive advantage when connecting design and technology developments, that is, the functional dimension of innovation (Kim and Kim, 2021; Rubera and Droge, 2013; Swan et al., 2005), this research indicates how the aesthetic and symbolic components of design play a role in innovation in a similar fashion. We therefore suggest that not only design connects with R&D in as far as the functional component is concerned (Barge-Gil et al., 2011), but that there exists a meaningful relationship between the more formalised, principle-driven components of a new product and those components driven by innovation in forms, symbols, and meanings. This relationship rests on the tacit nature of design know-how, driven by aesthetic or symbolic innovation, and is further testimony to extant arguments whereby these dimensions of design can bridge product engineering and technology with the market in terms of fulfilling user needs (Tether, 2005).

5.2 Policy and managerial implications

The findings yield meaningful policy and managerial implications. In terms of policy, while many manufacturers recognise the value of design, insufficient support for design-based innovation and limited recognition of the aesthetic and symbolic dimensions of design in industrial policies and strategies hinder firms' effort towards taking greater advantage of design (Rosenfeld, 2018). Our study indicates that policies aimed at supporting innovation could focus more comprehensively on the relationship between design activities, in their aesthetic and symbolic dimensions, and new product development (Gann and Salter, 2000; Sunley et al., 2010). Similarly, for managers, we show how design activities follow a knowledge-based process that can be strengthened through experience within firms. This research connects with recent contributions that urge firms to widen their understanding of what being design-oriented may entail (Björklund et al., 2020; Cantò et al., 2021). In turn, implementing design and product innovation as interdependent processes may lead to mutually reinforcing effects when jointly implemented. In particular, conceiving the aesthetic and symbolic dimensions of design innovation as an integral part of firms' innovation activities may yield learning effects across different organisational units (Gemser and Leenders, 2011; Micheli et al., 2018; Verganti, 2011).

5.3 Limitations and future research avenues

The findings presented should be considered vis-à-vis some limitations of the current research. First, our analysis rests on general proxies of innovation output in a similar fashion to previous studies based on innovation surveys (Filippetti, 2011; Montresor and Vezzani, 2020). In particular, our data do not provide more detailed information on the specific qualities of design innovation, which prevents us from exploring the differential impact of radical design innovation (Verganti, 2008, 2011). Similarly, whilst our results point to a positive role of external collaboration for design innovation, further studies may offer more specific quantitative evidence on this relationship (Dell'Era and Verganti, 2009). Second, our analysis does not allow to understand at which stage of the innovation process design and product innovation are connected and/or how design management can shape this process (Chiva and Alegre, 2009). Additional work is therefore required to better understand the role of design within complex innovation strategies, with the aim of better understanding the complementarities that may arise between design and other forms of innovation such as process or organisational innovation (Ballot et al., 2015; Battisti and Stoneman, 2010). While we focused on potential complementarities and learning effects between product and design innovation, further research is essential to understand whether these linkages may also generate synergistic effects for firms' performance (Ballot et al., 2015; Rubera and Droge, 2013). Drawing upon this research, we call for an exploration of the strategic and managerial efforts directed to effectively exploit synergies between design and other forms of innovation, complementing recent debates around the strategic role of design (Gallego et al., 2021; Knight et al., 2020). More broadly, we join recent research that aims at understanding how and under which circumstances we can capture and measure the value of design innovation (Dan et al., 2018; Filitz et al., 2015; Montresor and Vezzani, 2020).

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Tables and Figures

Table 1. Descriptive statistics

	Description	Mean	SD
PRODUCT INNOVATION	Introduced product innovation (new product or significantly different from previous)	0.17	0.38
DESIGN INNOVATION	Introduced innovation reflecting significant changes in the design or packaging of their products	0.11	0.31
R&D INTENSITY	Total R&D expenditure over firm turnover (log)	0.01	0.02
GRADUATES SHARE	Proportion of engineers and graduates	6.88	8.84
COOPERATION	Cooperated with: customers, suppliers, universities or technology centres	0.32	0.46
EXPORTS	Total value of exports (log)	10.06	7.21
FIRM AGE	Firm age	31.83	20.30
FIRM SIZE	Total number of employees	196.40	683.36

Table 2. Correlation matrix

PRODUCT INNOVATION	1						
DESIGN INNOVATION	0.32	1					
R&D INTENSITY	0.28	0.08	1				
GRADUATES SHARE	0.14	0.07	0.27	1			
COOPERATION	0.39	0.21	0.36	0.27	1		
EXPORTS	0.25	0.15	0.19	0.27	0.44	1	
FIRM AGE	0.09	0.08	0.06	0.17	0.20	0.26	1
FIRM SIZE	0.14	0.12	0.14	0.14	0.23	0.26	0.15

Table 3. Transition probability matrices

	One Year		Five Years		Ten Years	
	0	1	0	1	0	1
DESIGN INNOVATION						
0	95.12	4.88	94.00	6.00	91.06	8.94
1	39.90	60.10	57.35	42.65	62.35	37.65
PRODUCT INNOVATION						
0	92.52	7.48	89.29	10.71	91.00	9.00
1	33.23	66.77	47.21	52.79	57.93	42.07
DESIGN INNOVATION & PRODUCT INNOVATION						
0	97.01	2.99	96.46	3.54	96.43	3.57
1	48.15	51.85	64.08	35.92	81.82	18.18

Table 4. Firms introducing design and product innovations (%), by 2-digit NACE sector

NACE Sector	DESIGN INNOVATION	PRODUCT INNOVATION
1. Meat products	24.12	17.06
2. Food and tobacco	21.89	17.52
3. Beverage	28.81	14.13
4. Textiles and clothing	9.57	13.04
5. Leather, fur and footwear	10.43	13.5
6. Timber	4.03	7.89
7. Paper	6.23	13.48
8. Printing	2.06	4.42
9. Chemicals and pharmaceuticals	17.04	28.85
10. Plastic and rubber products	8.87	18.18
11. Nonmetal mineral products	8.74	13.4
12. Basic metal products	3.15	9.77
13. Fabricated metal products	4.82	9.42
14. Machinery and equipment	9.72	33.92
15. Computer products, electronics and optical	16.33	51.31
16. Electric materials and accessories	10.36	26.53
17. Vehicles and accessories	7.87	23.47
18. Other transport equipment	8.6	23.25
19. Furniture	11.44	17.02
20. Other manufacturing	9.49	16.67
Total	11.05	17.44

Table 5. Dynamic probit estimates for DESIGN INNOVATION

	(1)		(2)	
	Probit – Unbalanced Sample		Dynamic probit – Balanced sample	
	β	SE	β	SE
DESIGN INNOVATION$_{t-1}$	1.370***	(0.075)	1.043***	(0.077)
PRODUCT INNOVATION	0.863***	(0.056)	0.698***	(0.083)
R&D INTENSITY	0.285	(0.810)	0.753	(2.039)
GRADUATES SHARE	-0.001	(0.002)	-0.009	(0.006)
COOPERATION	0.227***	(0.057)	0.206**	(0.101)
EXPORTS	0.009**	(0.004)	0.026**	(0.013)
FIRM AGE	-0.001	(0.001)	0.101	(0.198)
FIRM SIZE	0.074***	(0.023)	0.082	(0.141)
Const	-1.871***	(0.134)	-4.298***	(1.373)
Obs	13601		7400	
N. Firms	2497		839	
Log PseudoL	-2905.95		-1523.88	
Wald Chi	1688.65 (***)		894.06 (***)	

* p<0.10 ** p<0.05 *** p<0.01 - Robust SE in parentheses. All regressions include time and industry dummies. Dynamic probit includes time averages and initial conditions.

Table 6. Dynamic bivariate probit estimates for DESIGN INNOVATION and PRODUCT INNOVATION

	(1)				(2)			
	Bivariate dynamic probit- Unbalanced sample				Bivariate dynamic probit- Balanced sample			
	DESIGN INNOVATION		PRODUCT INNOVATION		DESIGN INNOVATION		PRODUCT INNOVATION	
	β	SE	β	SE	β	SE	β	SE
DESIGN INNOVATION$_{t-1}$	1.731***	(0.055)			1.530***	(0.063)		
PRODUCT INNOVATION$_{t-1}$			1.598***	(0.046)			1.461***	(0.056)
DESIGN INNOVATION			0.325***	(0.054)			0.304***	(0.073)
PRODUCT INNOVATION	0.353***	-0.049			0.295***	(0.072)		
R&D INTENSITY	1.101	(0.706)	5.201***	-0.888	1.252	(1.800)	7.048***	(1.902)
GRADUATES SHARE	0.000	(0.002)	-0.002	(0.002)	-0.006	(0.005)	0.008	(0.005)
COOPERATION	0.321***	-0.050	0.654***	-0.047	0.233**	(0.097)	0.490***	(0.091)
EXPORTS	0.009**	(0.004)	0.011***	(0.003)	0.027*	(0.014)	0.021	(0.013)
FIRM AGE	-0.001	-0.001	0.000	(0.000)	0.043	(0.134)	-0.206*	(0.114)
FIRM SIZE	0.072***	(0.019)	0.068***	(0.018)	0.105	(0.131)	0.213*	(0.118)
Const	-1.867***	-0.119	-2.115***	-0.131	-3.104***	(0.773)	-2.372***	(0.665)
ρ	0.448 (0.058)***				0.404 (0.083)***			
Obs	13601				7400			
N. Firms	2497				839			
Log PseudoL	-6744.73				-3503.69			
Wald Chi	3345.24 (***)				2157.65 (***)			

* p<0.10 ** p<0.05 *** p<0.01 - Robust SE in parentheses. All regressions include time and industry dummies. Dynamic bivariate probit includes time averages and initial conditi

Table 7. System-GMM estimates for DESIGN INNOVATION and PRODUCT INNOVATIONDESIGN INNOVATIONPRODUCT INNOVATION

	DESIGN INNOVATION		PRODUCT INNOVATION	
	β	SE	β	SE
DESIGN INNOVATION$_{t-1}$	0.494***	(0.055)		
PRODUCT INNOVATION$_{t-1}$			0.440***	(0.110)
DESIGN INNOVATION			0.291**	(0.124)
PRODUCT INNOVATION	0.101**	(0.042)		
R&D INTENSITY	-0.46	(0.390)	3.095**	(1.575)
GRADUATES SHARE	0.000	(0.000)	0.007***	(0.002)
COOPERATION	-0.009	(0.024)	-0.147	(0.121)
EXPORTS	-0.001	(0.002)	0.019***	(0.007)
FIRM AGE	0.000	(0.000)	-0.001	(0.001)
FIRM SIZE	0.026**	(0.012)	0.010	(0.061)
Const	0.003	(0.045)	-0.14	(0.244)
Obs	13601		13601	
N. Firms	2497		2497	
F Statistic	31.07***		51.57***	
AR3 test (Prob > z)	0.78		0.11	
Hansen test (Prob > χ2)	0.15		0.93	

Instruments for first differences equation: DESIGN INNOVATION, PRODUCT INNOVATION, R&D INTENSITY, GRADUATES SHARE, COOPERATION. EXPORTS, FIRM SIZE; Instruments for levels equation: FIRM AGE, sector, time. * p<0.10 ** p<0.05 *** p<0.01 - Robust SE in parentheses. All regressions include time and industry dummies.

Figure 1. Companies introducing design and product innovations (%), 2007-2016

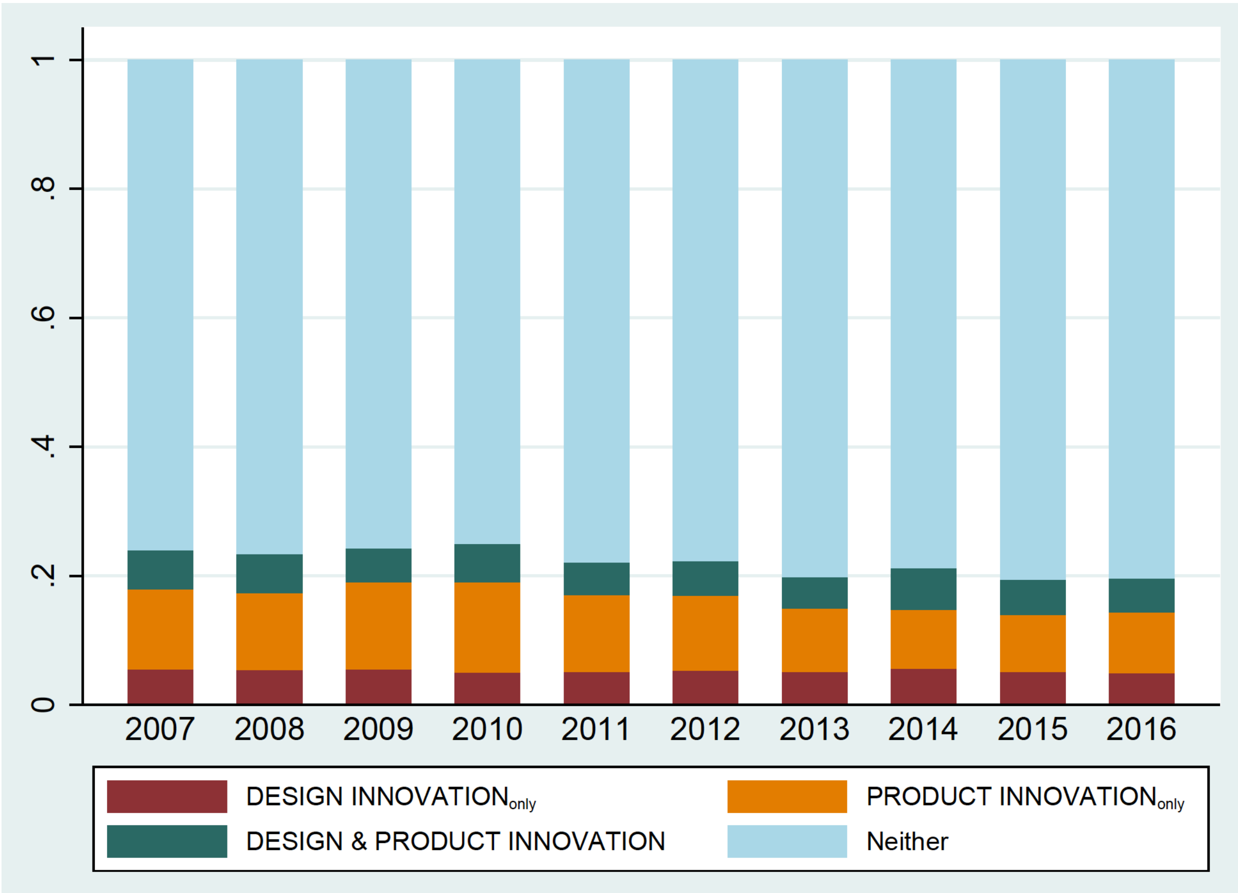

Figure 2. Predicted probabilities for DESIGN INNOVATION and PRODUCT INNOVATIONDESIGN INNOVATIONPRODUCT INNOVATION