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DISCUSSION PAPER

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Reverse Engineering and Innovation: Empirical Evidence From a High-Tech Economy

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Reverse Engineering and Innovation: Empirical Evidence from a High-tech Economy

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Abstract

Reverse engineering allows firms to learn about critical components and design features of competitors' technologies. Historically, reverse engineering has often been used to help technological laggards to catch-up and profit from other's inventions. However, through reverse engineering firms may also obtain knowledge that can be used for own innovation efforts beyond mere imitation, making it a relevant knowledge acquisition channel for technological leading firms in high-tech economies. Based on data from the German part of the Community Innovation Survey (CIS), this paper provides empirical evidence on the characteristics of firms that use reverse engineering, and whether reverse engineering can lead to superior innovation performance in terms of commercializing innovations with a high degree of novelty. Our results suggest that in the context of a high-tech economy, it is rather firms that operate under fierce price competition that use reverse engineering, helping them to obtain higher innovation output, though for innovations with a low degree of novelty.

JEL-Classification: O31, O33, D83

Keywords: Reverse engineering, knowledge spillovers, innovation output

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1 Introduction

Reverse engineering (RE) describes the process of analyzing technological objects in a way to learn about how the object has been designed and produced (Samuelson and Scotchmer 2002, Curtis et al. 2011, Raja and Fernandes 2007). RE is hence a mechanism to obtain knowledge from others and constitutes a special type of knowledge flow between firms (Harabi 1997). From the sender's point of view, RE is an unintended outflow of knowledge which can limit the profitability of own innovative efforts if RE leads to rapid imitation of technology (Roper et al. 2017). For a firm using RE, it can be an important mechanism to adopt others' technologies at low cost. In addition to imitating other's objects, RE can also facilitate complementary innovations in the RE using firm, from which both firms can benefit.

Reverse engineering constitutes a specific form of knowledge spillover, but has less intensively been studied than other sources, such as co-operation agreements, information from patents, or inter-firm knowledge transfer through individuals (Czarnitzki and Kraft 2012, Capelli et al. 2014, Terjesen and Patel 2017, Demircioglu et al. 2019, Audretsch and Belitzki 2022, Banal-Estañol et al. 2022). Historically, RE has frequently been used by technological laggards to catch-up and learn from technological leaders (Ohly 2009). RE is hence often considered in the context of economic development in catching-up countries as a strategy to increase productivity and international competitiveness with limited investment in the country's knowledge base and creative capacity (Minagawa et al. 2007, Gebremariyam et al. 2022, Zhang and Zhou 2016). In high-tech economies, RE has less frequently been looked at as a knowledge acquisition mechanism (Zedtwitz and Hadengue 2019), and is often regarded as a less advanced way of innovating that focuses on imitation rather than creating new solutions (Zhang et al. 2023).

Although RE has been used for a long time in the business world as a way to innovate, the empirical evidence on the scope, significance and effectiveness of RE as a knowledge transfer mechanism is still limited. This is especially true for RE in high-tech economies. The aim of this paper is to provide new empirical evidence on the role of RE for innovation in a high-tech economy, using Germany as case. We attempt to make two contributions to the literature: First, we analyze which types of firms use RE with respect to firm characteristics and strategies, and the business environment in which the RE using firms operate. Second, we investigate the contribution of RE to innovation performance, both in terms of the novelty level of innovations and the commercial success obtained from innovation.

We use the German part of the European Commission's Community Innovation Survey (CIS) as data base. The 2018 wave of the CIS contained a question on the use of different knowledge sources, including RE as one item. We combine this information with data on innovative capabilities, business strategies and the financial situation of firms and the firms' competitive environment in order to identify the characteristics of firms that use RE. In a second step, we link RE use and innovation results in terms of introducing product or process innovation (of different levels of novelty) and obtaining commercial returns from these innovations (sales of product innovations, cost reduction from process innovation). In order to tackle endogeneity issues, we employ matching and instrument variable approaches.

The empirical results show that using RE in the context of a high-tech country is positively related to both product and process innovation. For product innovation, RE stimulates the introduction of imitations of others' innovations and leads to higher sales with such innovations, which is in line with the view that RE is used to copy others' ideas and challenge original innovators. For process innovation, we find a strong link with cost reduction. This result is related to some specific characteristics of RE using firms. They tend to operate in a highly competitive environment, characterized by price pressure and strong competition from abroad. In addition, they are more credit constrained than other firms. At the same time, they follow a quality leadership business strategy. RE seems to be a viable approach for a small fraction of firms in high-tech economies (in Germany, about 6 percent of all firms) to keep pace with technological change in order to offer customers high-quality products while confining own development costs and realizing cost advantages through process innovation. Such RE-based strategies can be found both in manufacturing and services, with a stronger cost reduction focus in manufacturing and a stronger imitation focus in services.

In the next section, we discuss the theoretical background of RE and derive hypotheses that guide our empirical analysis. The methodology and data base of the empirical analysis is presented in section 3. Section 4 discusses the results on the determinants of RE use, while section 5 contains the findings on RE and innovation output. Section 6 concludes and derives implications for firms and policy makers.

2 Theoretical background

2.1 Reverse engineering

RE describes the process of extracting information from an object by decomposing it and analyzing its content, design features and technical specifications. Objects may include physical products, intangibles such as software, as well as processes and systems. From an economic point of view, RE is a mechanism to acquire knowledge from other firms. These other firms may be competitors of the RE using firm as well as suppliers, customers or firms not related to the RE using firm.

RE as a knowledge acquisition process usually involves four steps (see Samuelson and Scotchmer 2002), associated with different capabilities and resources required from the RE using firm. First, firms' have to be aware about objects that are worth and feasible to reverse-engineer. This requires an understanding of the value and potential of certain technologies by the firm attempting to reverse-engineer, as well as some market experience, since RE using firms will have to link the expectation about the feasibility and cost of RE with the likely returns that the firm might generate from the knowledge obtained through RE. The second step, information extraction, is the technical process to decompose and analyze others' objects (Bhatti et al. 2018). Usually, some in-depth knowledge about the underlying technologies and the functioning of the objects to be reverse-engineered is required for this step, which is related to the concept of absorptive capacity (Cohen and Levinthal 1990). A precondition for this step is to get access to the object to be reverse-engineered. For products offered in the market, this is usually straightforward, while processes or systems that others only use in-house are much more difficult to obtain and hence less frequently subject to RE.

In a third step, the knowledge obtained from RE is used for the firm's own purposes, e.g. by re-building the reverse-engineered object, or by developing, designing and producing own objects. In this step, additional knowledge is often crucial, e.g. which production technology is required to produce a reverse-engineered object achieving a certain level of quality. Fourth, the marketing step aims at obtaining economic returns from the RE effort, either by introducing products based on RE knowledge to the market, or by using the knowledge in-house in the firms' business processes. This step often involves decisions about the positioning, pricing and distribution of RE-based products in the market vis-à-vis other products.

The knowledge acquired through RE can be used for different purposes. In a development economics context, RE is often seen as a way to catch-up by learning from technologically advanced providers and copy their innovations for own use (see Minagawa et al. 2007, Gebremariyam et al. 2022, Zhang and Zhou 2016). In the context of high-tech economies, which is the focus of this paper, imitation is only one purpose of RE, though an important one (von Zedtwitz and Hadengue 2019). RE as an imitation strategy often aims to challenge the innovator by designing a similar product (while avoiding to violate the innovator's IP) that competes with the original innovation, potentially appropriating some of the innovator rent. Imitated products can also be used to supply regional or sectoral markets that are not targeted by the innovator (Kogut and Zander 1992, Malik and Kotabe 2009). For succeeding with this purpose of RE, RE using firm will have to overcome certain liabilities of followers, such as a lower reputation and difficulties to alienate customers of the original innovation due to lock-in and switching costs. At the same time, the RE using firm may challenge the innovator through a lower price based on lower development costs (Kopel and Löffler 2008).

In addition to imitating, RE may also be used for a number of other purposes. First, one can use RE to perform competitor analysis and to get ideas for own innovations, without necessarily copying the knowledge obtained from RE. In that way, RE is similar to other knowledge acquisition efforts of firms and may complement knowledge obtained from other sources such as patent files, trade fairs, trade publications, hiring of new staff or collaboration. Secondly, RE can be used to adjust one's own objects so that they better complement other objects (see Messler 2013, Eilam 2005). Typical examples include a better interoperability of own products with other products and to develop interfaces between products (Abbot 2003). From such type of RE both the innovator and the RE using firm may profit, since sales of products that better fit to each other will be more attractive to users, resulting in mutual stimulation of sales.

Thirdly, RE can help to identify potential weaknesses of objects, such as security gaps in software (Singh 2024) or quality issues (Elsayed et al. 2019). This knowledge can be important for effectively using these objects for one's own activities. This also applies to process technology that has to be integrated with other technology to form more complex production systems, as well as to materials or intermediary products that serve as inputs in the own production process (Pandilov et al. 2018). Fourthly, RE can be used to re-produce or replace objects that are no longer offered on the market. This is often the case for software that has been implemented long ago and that is not supported and maintained anymore or is not compatible to new software systems (Kienle and Müller 2010). RE can help to understand the original software and replace it by an up-to-date one. A related RE goal is repurposing, which describes the reuse of obsolete objects in a different-but-useful manner. Finally, RE can be employed to analyze whether intellectual property (IP) has been violated (Evans 2013). In this case, RE aims at identifying technical elements in objects that use protected IP. Such type of RE may be conducted by the IP owner, but can also be used by other firms, e.g. for learning how to avoid patent infringement when designing own products that rely on technology that is close to technologies protected by others.

These different purposes of RE in a high-tech context are critical for understanding the decision of a firm to use RE. This decision is determined by the relation between expected cost and expected returns of RE. While RE has the potential to speed up innovation processes and save development costs for the RE using firm by avoiding technological approaches that at the end turn out to not work, it can also go with high own development costs for the RE using firm. For example, complementary knowledge and technology may be required to effectively use RE results. Generating returns from RE will depend on a large number of factors, including which purpose RE should serve. In case imitation of competitors' innovations is the aim of RE, the speed of introducing the imitated product, the quality characteristics of the imitated products, the willingness of customers to switch from the original innovator to the imitator, and the innovators response strategy are critical factors which are hard to predict.

2.2 Research questions

The multitude of purposes for using RE implies that very different firms may engage in RE, including technologically leaders and laggards, as well as competitors, suppliers and customers of the firm whose object is reverse-engineered. The variety of RE uses is also associated with a variety of capabilities and resources that an RE using firm will have to command. This is particularly true in the context of a high-tech economy, where RE may focus less on imitation purposes and more on knowledge acquisition for other innovation objectives.

The aim of this paper is to better understand the role of RE for innovation in the context of a high-tech economy. Two main research questions guide the empirical analysis: Which type of firms engage in RE, and which type of innovations are linked to RE? The empirical investigation is explorative in nature, and not aimed at establishing causal relationships between RE, firm characteristics and innovation output. Since the decision to use RE is likely to be part of a firm's overall innovation and business strategy, simultaneity of RE, firm characteristics and innovation output is more likely than causality in the sense that a certain firm characteristic causes the use of RE, and the use of RE causes a certain innovation output.

For analyzing the characteristics of RE using firms, we consider four groups of factors. First, the literature suggests that using RE will require a certain in-house *technological capacity*, both to identify relevant technological objects for which an RE approach is feasible and economically promising, and for executing the RE task. Relevant technological capacities may include research and development (R&D) staff and laboratory equipment (Cohen and Levinthal 1989) as well as the breadth of technological competences among the firm's staff. Experience with IP issues, particularly related to patent law and how to avoid infringement of others' patents when using results from RE is another relevant capability.

Secondly, the *business strategy* a firm has adopted is likely to be linked to knowledge acquisition strategies, and hence to using or not using RE. On the one hand, RE may be used by firms that follow a strategy to offer high-quality products by rapidly adopting new technological trends in the markets ('quality leadership'), which are identified and acquired through RE. For these firms, RE can help to keep pace with new technological developments while effective RE allows to speed up development processes and offer customers always a high quality level. On the other hand, firms that aim at offering a broad range of products may be inclined to rely on RE since developing or improving different products at the same time through in-house R&D may exceed the financial and personnel resources available. Finally, RE may also be a promising approach for firms that aim at reaching out to new customer groups. In order to acquire new customers, these firms may rely on (technological) solutions of those firms that already serve these customers, and learn about these solutions through RE. At the same time, shorter development processes owing to RE can speed up time to market.

A third important factor is the firm's *market environment*. In many contexts, RE use may be linked to a more competitive market environment that urges firms to look for low-cost and rapid ways to update their offerings and realize cost advantages over competitors. This is particularly likely in case RE is used to imitate others' innovations and to challenge the original innovator. Such a market environment may be characterized by frequent market entries, a high price elasticity of demand, ease substitution of own products by competitor products, a rapid aging of products due to high technological dynamics, a strong competition from abroad, as well as high uncertainty about demand and competitors' actions. Finally, RE use may be linked to the *financial situation* of a firm. Since RE has the potential to save development costs compared to other knowledge acquisition channels such as cooperation or using codified knowledge from publications, patent files or digital sources, firms with lower financial resources may be more likely to opt for RE.

Concerning our second research question, the link between RE and innovation output, RE requires to be able to investigate an object in detail, which implies to legally acquire the object. This is usually straightforward for products offered in the market, and less easy for process technology and systems used in-house. For this reason, it is more likely that RE is linked to product rather than process innovation. With respect to the degree of novelty, RE used for imitation purposes will, by definition, result in imitations of the original innovator's object, implying a lower level of novelty. However, using RE as a general knowledge acquisition strategy aimed at deriving ideas for own innovations may result in real innovations with a high degree of novelty.

Concerning commercial success of innovations based on an RE approach, both higher and lower outcomes are possible, depending on the RE using firm's ability to quickly obtain relevant knowledge from the RE exercise, and to transfer this knowledge into own innovations that can compete with other offerings in the market. In general, higher commercial success is more likely for imitations of others' innovations, since RE using firms can profit from the experience of the original innovator in designing and marketing the product. With respect to process innovation, firms using RE to adopt others' process technology may benefit from efficiency gains as they will rely on proofed technology that has been effectively used by others, hence avoiding technological solutions that will turn out to be ineffective or inefficient.

An important pre-condition for RE is to have access to the object to be reverse-engineered. This is likely to be easier for physical products than for services or intangible objects. For this reason, it is not only likely that RE use will be more frequent in manufacturing than in services, but also the characteristics of RE using firms may differ significantly. For this reason, we investigate the link between RD, firm characteristics and innovation separately for manufacturing and service industries.

3 Empirical strategy and data

3.1 Empirical strategy

For investigating the research questions discussed above, we estimate two empirical models, [1] a model of the determinants of RE and [2] an innovation output model that includes RE as an input. The model set up can be written as follows:

$$RE_{\mathrm{i}} = \alpha + \beta_1\, TC_i + \beta_2\, BS_i + \beta_3\, ME_i + \beta_4\, FS_i + \beta_5\, CT_i + \varepsilon_i \qquad [1]$$

$$IO_{\mathrm{m,i}} = \alpha_m + \beta_{6m}\, RE_i + \beta_{7m}\, IN_i + \beta_{8m}\, KS_i + \beta_{9m}\, CT_i + \varepsilon_{m,i} \qquad [2]$$

For the RE model, three groups of determinants along with a set of control variables (*CT*) are included: *TC* captures the technological capacity of a firm *i*, *BS* the business strategy, *ME* the market environment, and *FS* the financial situation. For the *IO* model, different types of innovation output *m* are distinguished, including product vs. process innovation, the degree of novelty of a product innovation, and the economic returns obtained from innovation (sales with product innovation, cost reduction from process innovation). The independent variables of the *IO* model cover innovation input (*IN*), other knowledge sources used by the firm (KS) and a set of control variables and *RE*. α is a constant, β are the coefficients to be estimated and ε is an error term. Since the dependent variable in model [1] is a binary variable, a probit regression is used. Model [2] is estimated by tobit regressions for indicators of the introduction of innovations, and by tobit regressions for the commercial success of innovations (reflecting the fact that many firms show zero commercial success in case no product or process innovations have been introduced).

In order to limit potential endogeneity between innovation output and a firm's decision to use RE, we employ two alternative approaches. A matching approach is used to balance RE using and not RE using firms with respect to variables that are correlated with the firms' decision to use RE. We employ the entropy balancing approach of Hainmueller (2012) and derive weights for each firm that ensure that the mean, standard deviation and skewness of all variables in model [1] do not differ significantly for the samples of RE using and not RE using firms after weighting. The weights are then used to estimate model [2].

As a second, alternative approach, we employ an instrument variable (IV) method for identifying the contribution of RE to innovation output (see Angrist and Pischke 2009, Abadie and Cattenao 2018). A common problem of IV approaches is the lack of adequate instruments. This is also the case for our study, as potential instruments are often correlated with both RE and the innovation outcome. We therefore use Lewbel's approach, which employs internally generated instruments. These instruments are based on the existence of heteroskedasticity, i.e. the variance of the disturbance term differs between the individual observations. Instruments are generated by interacting the regressors with the residuals of the estimation in the first stage. These interaction variables serve then as instruments in the second stage of the estimation, so that no exogenous instrumental variables are needed. Lewbel (2018) discusses the application of his estimator to the binary variable case. The Lewbel model is now used increasingly in research (e.g., Araki et al. 2024, Courtemanche et al. 2021, Li et al. 2022, Loy et al. 2016, Umberger et al. 2015, Wang and Cheng 2022). The estimation of a dependent binary variable with the help of another endogenous binary variable is not trivial. Angrist and Pischke (2009) suggest using a standard linear 2SLS model and we follow this idea.

3.2 Data

Our data basis is the German part of the Community Innovation Survey (CIS). The German CIS is a panel survey conducted annually by the Center for European Economic Research (ZEW, Mannheim, Germany) on behalf of the German Federal Government and is also known as Mannheim Innovation Panel (MIP; see Peters and Rammer 2023 for more details on the survey). The survey fully complies with the methodological recommendations and quality requirements for official business statistics as laid down by the European Statistical Office and employs the concepts and definitions for measuring innovation in the business enterprise sector described in the Oslo Manual (OECD and Eurostat 2018).

The panel survey includes both regular questions (asked in every survey wave) and one-off questions that are included only in a specific survey year. The survey for the reference year 2018 (CIS 2018) included such a one-off question on various external knowledge sources that a firm can use for its business activities, covering eight sources: scientific/trade publications, patent files, standardization documents, social media/networks, open source software, trade fairs, reverse engineering, and employing new staff. For each source, firms indicated whether they used this source to acquire knowledge of others during a three year reference period (2016 to 2018).

In the 2018 MIP survey, 38,902 firms were contacted (excluding firms with outdated contact details or that ceased business), of which 8,093 provided valid responses by filling in either the online form or the paper version of the questionnaire, resulting in a response rate of 21.2%. In order to examine a likely bias among responding and non-responding firms, a comprehensive non-response survey was conducted. A random sample of non-responding firms (covering 10,172 firms, i.e. 33.9% of all non-responding firms) were interviewed via telephone to collect some basic data on their innovation activities. The results show that 54.3% of non-responding firms were innovators, compared to 64.9% of responding firms, suggesting a significant survey bias towards innovative firms. In order to adjust for this bias, weights were calculated for each responding firm in a way that weighted results produce the 'true' share of innovators among both responding and non-responding firms (see Behrens et al. 2017 for details on the weighting procedure).

3.3 Descriptive results on the use of RE

The key variable in our analysis, reverse engineering (*Reverse*), is measured as a binary variable that indicates whether a firm used, during the three-year reference period 2016 to 2018, reverse engineering to acquire knowledge from others. In the German enterprise sector covered by the CIS, 6.3% of all firms used RE as a way to obtain knowledge from others during 2016 and 2018 (Table 1). The share is higher in manufacturing (8.1%) than in services (4.7%). Innovation active firms more frequently use RE (8.5%) compared to not innovation active firms (1.6%). Compared to other knowledge acquisition channels, RE is rather rarely used. For example, more than 60% of all firms use fairs and exhibitions or scientific and trade publications for obtaining external knowledge (see Table 2). About a third of all firms us digital sources such as social media, and 10 to 20% use patents, standardization documents or the hiring of staff from other firms.

Table 1: Share of firms using RE to obtain knowledge from others (2016-2018, selected EU countries)

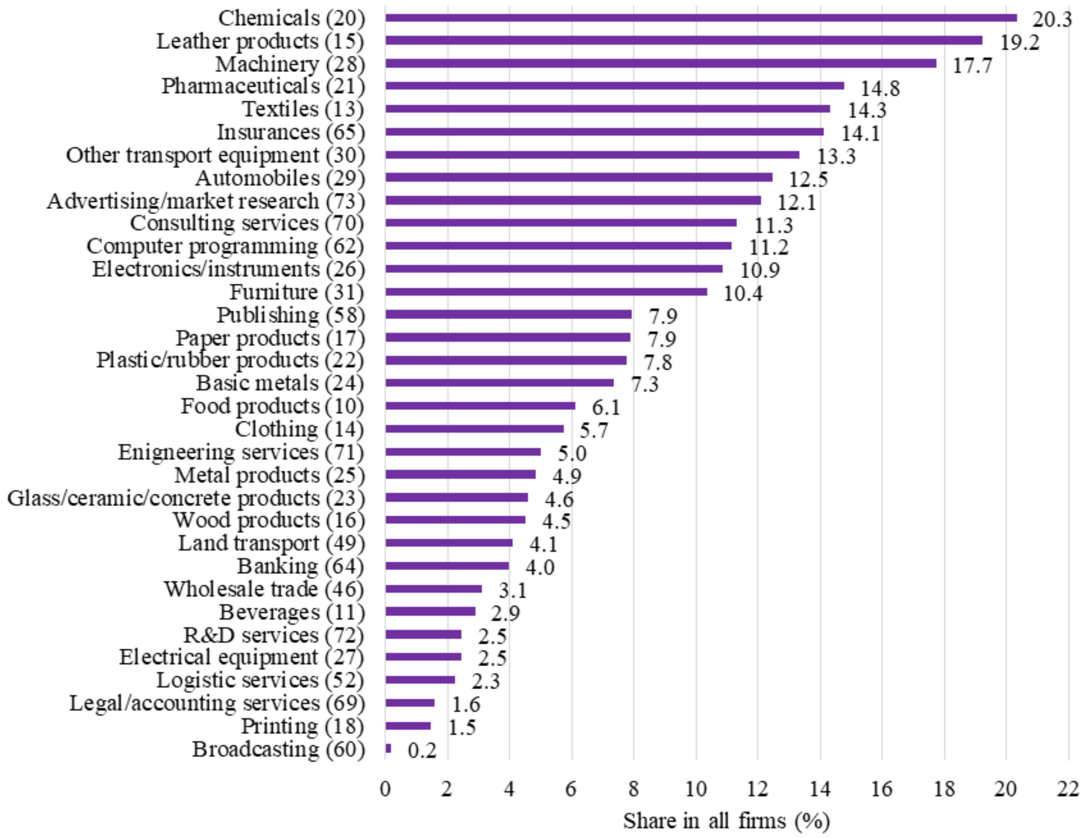
	Manufacturing			Services			Total		
Country	all	inn	n-inn	all	inn	n-inn	all	inn	n-inn
Germany	**8.1**	**10.5**	**1.9**	**4.7**	**6.6**	**1.4**	**6.3**	**8.5**	**1.6**
Austria	10.0	14.2	1.5	6.4	9.7	1.7	7.9	11.6	1.6
Bulgaria	10.6	23.5	3.7	9.8	26.4	4.4	10.2	24.6	4.1
Croatia	6.9	10.8	2.7	4.8	8.2	1.1	5.9	9.6	1.9
Estonia	7.4	9.7	0.7	3.6	4.3	1.9	5.5	7.0	1.3
Finland	19.7	26.2	6.7	10.9	16.9	2.4	14.6	21.2	4.0
France	9.9	15.7	2.5	9.7	16.2	3.8	9.8	15.9	3.3
Greece	12.3	17.2	4.3	8.4	13.1	1.7	10.0	14.8	2.7
Hungary	14.2	29.3	8.2	13.5	29.8	6.9	13.8	29.5	7.5
Italy	12.2	15.9	5.3	8.7	12.2	3.6	10.9	14.6	4.6
Lithuania	7.4	11.6	2.2	5.5	8.2	3.0	6.3	9.8	2.7
Luxembourg	14.3	19.4	7.1	7.9	13.3	2.8	9.1	14.5	3.4
Malta	17.0	31.4	4.8	13.1	24.9	2.7	14.2	26.7	3.3
Poland	4.7	12.4	1.9	3.5	10.5	1.6	4.1	11.6	1.8
Portugal	9.2	18.2	3.7	7.4	12.3	4.4	8.4	15.8	4.0
Romania	8.8	21.6	6.2	6.3	14.3	5.1	7.5	18.3	5.7
Slovenia	22.9	35.9	8.4	15.3	24.3	8.0	19.1	30.7	8.2

Weighted results for firms with 10 or more employees.
Manufacturing: NACE (rev. 1) 5 to 39; Services: NACE (rev. 1) 46, 49 to 53, 58 to 66, 71 to 73; Total: manufacturing and services; all: all firms; inn: innovation active firms; n-inn: not innovation active firms.
Source: Eurostat, CIS 2018

Compared to other EU countries for which data on RE use have been published, the share in Germany is rather low. Other high-tech countries such as Finland (14.6%), Austria (7.9%) and France (9.8%) report higher shares. EU countries with a less pronounced high-tech orientation report shares of RE using firms at a similar level than high-tech oriented countries do.

There are significant differences in RE use across industries (Figure 1). The highest share are reported for some manufacturing industries (chemicals, leather products, machinery, pharmaceuticals), where 15 to 20% of all firms rely on RE as a knowledge acquisition mechanism. There are also some service industries showing relatively high shares of RE using firms, including insurances, advertising, consulting, computer programming. It is likely that much of RE activities in these service industries is related to software RE. Industries with very low shares of RE using firms include both some manufacturing industries (printing, electrical equipment, beverages) and several service industries, such as broadcasting, legal and accounting services, logistic services, R&D services and wholesale trade.

Figure 1: Share of firms using RE to obtain knowledge from others, by selected industries (Germany, 2016-2018)



Weighted results for firms with 10 or more employees. NACE (rev. 1) codes in brackets.
Source: German Innovation Survey 2018

3.4 Measurement of model variables

For the innovation output model, we distinguish product innovation (*Pd*) and process innovation (*Pc*). For product innovation, we use three variables to determine the degree of novelty, following standard definitions of the Oslo Manual and the CIS which have been frequently used in the literature (see Rammer et al. 2022): new-to-world innovation (*Wnov*), market novelties not new to the world (*Rnov*), and product innovations that are not new to the market ('imitations' - *Imit*). In addition, we aggregate *Wnov* and *Rnov* to any kind of market novelty (*Mnov*). For process innovation, we distinguish process innovation that led to cost reduction (*Cost*) and other types of process innovation (*Othpc*), e.g. targeting quality improvements (Rammer 2023). All variables refer to innovations introduced during 2016 and 2018. For the commercial success obtained from innovations, we use the share of sales generated by product innovations (*Pd_s*), split by degree of novelty (*Wnov_s, Rnov_s, Mnov_s*) and the share of unit cost reduction resulting from process innovations (*Pc_s*) (see Piening and Salge 2015). Commercial success of innovation is measured for the year 2018 and relates to innovations introduced during 2016 and 2018. As an alternative measure for novelty, we consider the technological novelty of equipment that has been purchased by a firm, distinguished three novelty levels with respect to the technological state of equipment that has been used by the firm before: same state of technology (*Techsame*), improved technology (*Techimpr*) and entirely new technology not used by the firm before (*Technew*).

To analyze the characteristics of RE using firms, we include several measures for technological capabilities, business strategies, the firm's market environment, and the firm's financial situation. To capture a firm's in-house capabilities for developing and mastering technologies, we use indicator variables for continuous and occasional in-house R&D activities (*RD_con, RD_occ*), the past use of patents to protect one's own IP (*Patuse*) and the share of employees with a university degree as a general human capital indicator (*HC*). For measuring a firm's business strategy, we rely on a CIS question that asks firms about the importance of different potential business strategies they might follow. We build three business strategy indicator variables, considering firms that stating high or medium importance for the following strategies: focusing on quality leadership (*BS_qual*, as opposed to price leadership), focusing on offering a broad range of products (*BS_broad*, as opposed to focus on a few core products), and focusing on reaching out to new customer groups (*BS_newc*, as opposed to focus on existing customers).

A firm's market environment is characterized by the following six variables, derived from a question that asked firms to indicate the extent to which a set of characteristics describe the competitive situation in their market (considering firms for which the characteristics fully or mainly apply): threat by market entrants (*ME_entr*), high price elasticity of demand

(*ME_elas*), easy substitution of own products by competitor products (*ME_subs)*, rapid product aging or difficult to foresee technological developments (*ME_dyn*), high uncertainty in the product market with respect to competitor behavior or demand development (*ME_unct*), and strong competition from abroad (*ME_abr*).[1]

The financial situation of firms is measured through three indicators. A firm's credit rating published by Germany's largest credit rating agency (Creditreform) is a major determinant for a firm's access to external financing (*Credrat*). The information is provided directly by Creditreform to ZEW (see Bersch et al. 2014). We use the credit rating for the starting year of the three-year observation period to which our RE measure refers to (i.e. 2016). In addition to the credit rating, Creditreform recommends a maximum credit line for each firm, which takes into account, among others the availability of collaterals and the current debt ratio of a firm. We relate this figure to the firm's annual sales to adjust for firm size, and use the 2016 reference year (*Credsal*). From the CIS questionnaire, we derive a measure of credit constraints from a question on obstacles that have impeded the firm's innovation activities during 2016 and 2018. We consider firms to be credit constrained in case they indicate that a lack of external financial sources resulted in delaying, stopping or not starting innovation activities (*Credcon*).

In both models, we control for the age (*Age*) and the size (*Size*) of the firm and whether the firm is part of an enterprise group (*Group*). Age gives the number of years since the firm has been founded. Size is measured by the number of full-time employees. Since both age and size effects are likely to be non-linear, we use the logarithmic transformation. For model (2), we control for innovation input, measured by the amount of R&D expenditures per full-time employee (*RDint*) and the amount of non-R&D expenditure per full-time employee (*nRDint*).

[1] Note that some items on the market environment were merged because of high correlation, in order to avoid multicollinearity issues in model estimations.

Non-R&D expenditure include expenditure related to the development and implementation of innovations such as investment in capital goods and software, acquisition of external knowledge (e.g., patents, licenses), employee training, expenses for marketing and design, and preparing the production and distribution of innovations.

In the innovation output model, we also include other sources of external knowledge used by the firm, in order to avoid an omitted variable bias, since any type of knowledge acquisition can contribute to a firm's innovation performance. We consider seven other channels: trade fairs and exhibitions (*Fair*), publications in scientific or trade journals (*Publ*), patent files (*Patfile*), standardization documents (*Stand*), employing staff from other firms (*Hiring*), social media, other social networks or open source software (*Digit*), and cooperation agreements (*Coop*).

For estimating models [1] and [2], we restrict the sample to observations with full information on all model variables, resulting in a total number of 5,934 observations for model [1], 5,000 for model [2] on indicators of the introduction of innovations, and 4,907 for model [2] on indicators of commercial success with innovations. Definitions and descriptive statistics for all model variables are shown in Table 2. Descriptive statistics for RE using firms and for manufacturing and services sub-samples are reported in Table 8 in the Appendix.

Table 2: Definition and descriptive statistics of model variables

Variable	Definition	Mean	Std.Dev.	Min	Max
Model [1]					
Reverse	1 if firm acquired external knowledge through reverse engineering during 2016 and 2018, 0 otherwise	0.066	0.249	0	1
RD_con	1 if firm conducted in-house R&D continuously during 2016 and 2018, 0 otherwise	0.232	0.422	0	1
RD_occ	1 if firm conducted in-house R&D occasionally during 2016 and 2018, 0 otherwise	0.120	0.325	0	1
Patuse	1 if firm used patents to protect own IP, 0 otherwise	0.147	0.354	0	1
HC	Share of graduated employees	0.253	0.291	0	1
BS_qual	1 if competitive strategy "quality leadership" is of high or medium importance, 0 otherwise	0.902	0.298	0	1
BS_newc	1 if competitive strategy "approaching new customers" is of high or medium importance, 0 otherwise	0.610	0.488	0	1

BS_broad	1 if competitive strategy "offering a broad range of goods/services" is of high or medium importance, 0 otherwise	0.414	0.493	0	1
ME_entr	1 if market environment "major threat to market position of because of new market entrants" applies fully or mainly, 0 otherwise	0.470	0.499	0	1
ME_subs	1 if market environment "products are easy to be substituted by competitor products" applies fully or mainly, 0 otherwise	0.571	0.495	0	1
ME_elas	1 if market environment "price increase leads to immediate loss of customers" applies fully or mainly, 0 otherwise	0.464	0.499	0	1
ME_dyn	1 if market environment "products become outdated quickly" or "technological development difficult to foresee" applies fully or mainly, 0 otherwise	0.441	0.497	0	1
ME_unct	1 if market environment "actions of competitors difficult to predict" or "demand development difficult to predict" applies fully or mainly, 0 otherwise	0.696	0.460	0	1
ME_abr	1 if market environment "strong competition from abroad" applies fully or mainly, 0 otherwise	0.337	0.473	0	1
Credsal	Maximum credit line recommended by the credit agency *Creditreform* per annual sales	0.015	0.016	0	0.167
Credrat	Credit rating by the credit agency *Creditreform* (0= worst, 5=best)	3.688	0.461	1	5
Credcon	1 if firm was hampered in conducting innovation activities by a lack of external financing sources, 0 otherwise	0.187	0.390	0	1
Age	Age of the firm in years (log)	3.109	0.852	-0.693	6.039
Size	No. of full time employees (log)	3.164	1.587	-0.693	11.977
Group	1 if a firm belongs to an enterprise group, 0 otherwise	0.294	0.456	0	1
Model [2]					
Pd	1 if product innovation during 2016 and 2018, 0 otherwise	0.381	0.486	0	1
Imit	1 if product innovation is only new to the firm but not new to the market, 0 otherwise	0.349	0.477	0	1
Mnov	1 if product innovation new to the market during, 0 otherwise	0.116	0.320	0	1
Rnov	1 if product innovation new to a regional market, 0 otherwise	0.088	0.283	0	1
Wnov	1 if product innovation new to the world market, 0 otherwise	0.053	0.224	0	1
Pc	1 if process innovation during 2016 and 2018, 0 otherwise	0.556	0.497	0	1
Cost	1 if process innovation that led to unit cost reduction, 0 otherwise	0.165	0.371	0	1
Othpc	1 if process innovation did not lead to unit cost reduction, 0 otherwise	0.391	0.488	0	1
Technew	1 if newly acquired equipment represents technology not used by the firm before, 0 otherwise	0.164	0.370	0	1
Techimpr	1 if newly acquired equipment represents improved technology compared to the technology used by the firm before, 0 otherwise	0.574	0.495	0	1
Techsame	1 if newly acquired equipment represents the same state of technology as the technology used by the firm before, 0 otherwise	0.276	0.447	0	1
Pd_s	Sales share of product innovations in 2018	8.691	18.435	0	100
Imit_s	Sales share of product innovations that were only new to the firm	6.962	15.832	0	100
Mnov_s	Sales share of product innovation that were new to the market	1.730	8.592	0	100
Rnov_s	Sales share of product innovation that were new to a regional market	0.897	5.462	0	100
Wnov_s	Sales share of product innovations that were new to the world market	0.833	6.426	0	100
Cost_s	Share of unit cost reduction from process innovation in 2018	1.464	4.888	0	80
RDint	R&D expenditure per full time employee in 2018 (1,000 €)	2.431	7.685	0	51.8

nRDint	Innovation expenditure other than R&D per full time employee in 2018 (1,000 €)	0.933	3.175	0	23.2
Fair	1 if firm acquired external knowledge through trade fairs or exhibitions during 2016 and 2018, 0 otherwise	0.640	0.480	0	1
Publ	1 if firm acquired external knowledge from publications in scientific or trade journals during 2016 and 2018, 0 otherwise	0.676	0.468	0	1
Patfile	1 if firm acquired external knowledge from patent files during 2016 and 2018, 0 otherwise	0.097	0.295	0	1
Standard	1 if firm acquired external knowledge from standardization documents during 2016 and 2018, 0 otherwise	0.172	0.378	0	1
Hiring	1 if firm acquired external knowledge through employing staff from other firms during 2016 and 2018, 0 otherwise	0.215	0.411	0	1
Digit	1 if firm acquired external knowledge from social media, other social networks or open source software during 2016 and 2018, 0 otherwise	0.342	0.474	0	1
Coop	1 if firm cooperated with other firms or organizations during 2016 and 2018, 0 otherwise	0.269	0.443	0	1

Source: MIP 2018.

4 Results

4.1 Firm characteristics and RE

As discussed in the research questions section, the multitude of purposes for using RE in a high-tech country context implies that very different firms may use RE. We hence apply an explorative analysis that tests different potential characteristics in a three-step procedure. First, we estimate the determinants model [1] for each of the four groups of characteristics (TC, BS, ME, FS) separately. The results are shown in columns (1) to (4) of Table 3. In a second step, we estimate a determinants model including all four groups of characteristics, and split by manufacturing and services (columns 5, 5a and 5b). In the final step, we exclude all model variables that turned out to be insignificant to arrive at our final estimations (columns 6, 6a and 6b), which are also the basis for the matching approach used when analyzing the link between RE and innovation output (see Section 5).

Concerning technological capabilities, we find clear evidence that using RE requires absorptive capacities in terms of in-house R&D, while IP experience (use of patents) and the general human capital of a firm (share of graduates among employees) are not linked to RE.

Interestingly, the relevance of in-house R&D does not differ across firms conducting R&D on a continuous basis (i.e., having a separate R&D unit or employing dedicated staff for R&D) or only occasionally. For each group of firms, the probability of using RE is about 5 percentage points higher. Since the average share of RE using firms in the sample is 6.6 percent, this is a very strong relation, which holds for both manufacturing and services.

Table 3: Reverse engineering and firm characteristics: results of Probit estimations

	Total (1)	*Total (2)*	*Total (3)*	*Total (4)*	*Total (5)*	*Manuf. (5a)*	*Services (5b)*	*Total (6)*	*Manuf. (6a)*	*Services (6b)*
RD_con	0.062***				0.051***	0.049***	0.052***	0.052***	0.055***	0.049***
	(0.012)				(0.011)	(0.015)	(0.015)	(0.010)	(0.015)	(0.014)
RD_occ	0.066***				0.055***	0.048***	0.062***	0.056***	0.053***	0.060***
	(0.014)				(0.013)	(0.017)	(0.019)	(0.013)	(0.018)	(0.019)
Patent	-0.000				-0.001	0.002	-0.006			
	(0.008)				(0.008)	(0.011)	(0.010)			
HC	0.010				0.011	0.034	-0.001			
	(0.014)				(0.013)	(0.025)	(0.012)			
BS_qual		0.023**			0.018*	0.028*	0.010	0.020**	0.031**	0.012
		(0.010)			(0.010)	(0.015)	(0.010)	(0.009)	(0.014)	(0.010)
BS_newc		0.009			0.008	0.003	0.013*			
		(0.007)			(0.006)	(0.010)	(0.007)			
BS_broad		0.010			0.000	0.002	-0.000			
		(0.006)			(0.006)	(0.010)	(0.007)			
ME_entr			-0.000		0.002	-0.002	0.006			
			(0.007)		(0.006)	(0.009)	(0.007)			
ME_subs			0.003		0.005	0.014	-0.002			
			(0.007)		(0.006)	(0.009)	(0.007)			
ME_elas			0.019***		0.018***	0.013	0.022***	0.019***	0.016*	0.022***
			(0.007)		(0.006)	(0.010)	(0.008)	(0.006)	(0.009)	(0.008)
ME_dyn			0.015**		0.010*	0.010	0.009	0.010*	0.012	0.009
			(0.006)		(0.006)	(0.009)	(0.007)	(0.006)	(0.009)	(0.007)
ME_unc			0.002		-0.002	0.002	-0.006			
			(0.007)		(0.007)	(0.010)	(0.008)			
ME_abr			0.019**		0.012*	0.019*	0.006	0.014**	0.021**	0.007
			(0.007)		(0.007)	(0.010)	(0.008)	(0.007)	(0.010)	(0.008)
Credsal				-0.643**	-0.532**	-1.139**	-0.157	-0.532**	-0.955**	-0.232
				(0.268)	(0.245)	(0.457)	(0.221)	(0.243)	(0.435)	(0.235)
Credrat				0.001	0.000	0.013	-0.007			
				(0.008)	(0.007)	(0.011)	(0.008)			
Credcon				0.024***	0.013	0.023*	0.003	0.014*	0.026**	0.003
				(0.009)	(0.008)	(0.013)	(0.009)	(0.008)	(0.012)	(0.009)
Age	-0.000	-0.002	-0.002	0.001	0.001	0.006	-0.004	0.001	0.007	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)
Size	0.008***	0.011***	0.011***	0.010***	0.005**	0.005	0.005*	0.005**	0.006*	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)
Group	0.017**	0.023***	0.019**	0.024***	0.015**	0.014	0.015*	0.015**	0.015	0.015*
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.011)	(0.009)	(0.007)	(0.011)	(0.009)
# obs.	5,934	5,934	5,934	5,934	5,934	3,099	2,835	5,934	3,099	2,835

Marginal effects of Probit models with robust standard errors (standard errors in parentheses). All models include industry fixed-effects. ***, **, *: significant at p<0.01, p<0.05, p<0.1.

This result is somewhat different to the finding of Audretsch and Belitzki (2022) who argue that imitating others' innovations requires only some own R&D. Our result may be linked to the fact that not all RE is focusing on imitation, but RE may also be used to stimulate own technological development activities. The insignificant result for patent use suggests that RE use in German firms is not focused on IP-related purposes of RE.

For the firms' business strategy, we find a significant association between a quality-oriented strategy ('quality leadership') and RE use, which only holds for manufacturing, however. For services, there is a weakly significant link with RE for a business strategy that focuses on reaching out to new customers. Firms that focus their strategy on offering a broad range of goods or services do not show a higher or lower probability to use RE. This result suggests that RE is used in manufacturing firms to keep pace with technological change and maintain a high quality level of products by learning from the technological solutions offered by other firms. In services, in contrast, service quality seems less a motivation for RE use, which is rather linked to addressing new customers by offering services similar or complementary to those of other firms.

From the six indicators of a firm's competitive environment, three show a significant relation with RE use. The strongest link exists for a market environment characterized by a high price elasticity of demand. This link is stronger in services than in manufacturing. A strong competition from abroad is also positively associated with RE use, though only at a statistically significant level in manufacturing. For firms operating in a dynamic market environment (short product life cycles, rapid technological change), we find a weakly significant link to RE use. The other three variables for the competitive environment (high thread by market entrants, ease of substitutability, high uncertainty), no significant results emerged. All in all, RE use seems to be associated with a more competitive market environment, suggesting that RE helps firms that are under price pressure to maintain competitive.

In line with this finding is the result for a firm's financial situation, since firms with a less comfortable financial situation are more likely to use RE. This result holds for the indicator on the maximum recommended credit line as well as for the firm's self-perceived credit constraint, but only applies to firms in manufacturing. Using RE is hence a choice that is more appealing to credit constrained firms.

With respect to our control variables, firm age is insignificant, while larger firms and firms belonging to a corporate group are more likely to use RE.

4.2 RE and innovation output: matching approach

For analyzing the link between RE and innovation output, we employ both a matching and an instrument variable approach in order to address likely endogeneity resulting from the fact that certain firm characteristics and features of a firm's market environment determine both the propensity to use RE, and innovation output. We first report the results of the matching approach based on entropy balancing (EB). EB ensures that the characteristics that drive a firm's decision to use RE do not differ among RE using and not RE using firms, by weighting firms of each group accordingly (see Hainmueller 2012). The matching variables include all variables of the determinants model reported in column (6) in Table 3. The three statistical moments of all matching variables before and after matching are reported in Table 9 in the Appendix. In all regression analyses in this section, firms are weighted with EB weights derived from the EB matching. First, we present the results of Probit estimations for product and process innovation and the technological novelty of newly acquired equipment, followed by the results of Tobit estimations on the commercial success of innovations.

The estimation results for product and process innovation and technological novelty of acquired equipment are presented in Table 4. For product innovation, four types representing different levels of novelty are distinguished, ranging from imitation to new-to-world. The use of RE shows a positive and statistically significant correlation with product imitations. These are new or improved products which are only new to the innovating firm, but not new to the market, i.e. competitors were offering the same or a similar product in the market when the innovating firm introduced its new or improved product. The estimated marginal effect shows that an RE using firm has a 10 percentage points higher probability to introduce an imitation (the average share of firms with imitations is at 35 percent). For market novelties, regardless of the geographical reference region of the novelty, no statistically significant results are found. For process innovation, we find a strong link between RE use and the introduction of new or improved processes that reduce cost, while the link to other types of process innovation (e.g., those improving the quality of the outcome of a process, see Rammer 2023) is negative.

The results for both product and process innovation suggest that RE goes together with rather incremental and cost-oriented innovations. This is consistent with the finding that RE using firms operate in a competitive environment characterized by price pressure and strong international competition, and that RE using firms are credit constrained. The close link to imitations fits well with the result of a quality leadership strategy. Firms use RE to acquire others' technologies in order to offer high-quality products at a competitive price.

Table 4: Reverse engineering and introduction of innovations: results of Probit estimations (marginal effects) using EB-based weights

	Product innovation					Process innovation			Acquisition of Technology		
	Total (*Pd*)	Imitation (*Imit*)	Market novelty: Total (*Mnov*)	Market novelty: Regional (*Rnov*)	Market novelty: World-first (*Wnov*)	Total (*Pc*)	Cost reduction (*Cost*)	Other (*Othpc*)	Entirely New (*Technew*)	Improved (*Techimp*)	Same (*Techsam*)
Reverse	0.065**	0.094***	0.027	0.020	0.002	0.031	0.092***	-0.068**	0.068**	0.059**	0.038
	(0.033)	(0.032)	(0.027)	(0.023)	(0.014)	(0.026)	(0.030)	(0.031)	(0.029)	(0.028)	(0.031)
RDint	0.005*	0.003	0.003**	0.002**	0.002***	-0.002	-0.004**	0.002	0.001	-0.002	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
nRDint	0.023***	0.020***	0.007*	0.005**	0.001	0.021***	0.015***	-0.001	0.009***	0.008**	-0.004
	(0.007)	(0.005)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Fair	-0.006	0.033	0.014	0.015	-0.006	0.049	0.032	0.049	0.044	0.083**	0.027
	(0.041)	(0.045)	(0.037)	(0.033)	(0.025)	(0.034)	(0.040)	(0.043)	(0.041)	(0.042)	(0.044)
Publ	-0.025	-0.042	-0.036	-0.018	-0.058**	0.127***	0.018	0.137***	0.037	0.105***	0.048
	(0.042)	(0.043)	(0.040)	(0.035)	(0.029)	(0.040)	(0.040)	(0.038)	(0.042)	(0.040)	(0.043)
Patfile	0.133***	0.071	0.164***	0.053	0.105***	0.091***	0.089**	-0.009	0.036	0.045	-0.038
	(0.047)	(0.048)	(0.042)	(0.034)	(0.028)	(0.035)	(0.045)	(0.046)	(0.042)	(0.039)	(0.043)
Standard	-0.017	0.006	-0.023	-0.029	0.022	0.002	-0.012	0.004	0.040	0.036	0.062*
	(0.044)	(0.042)	(0.031)	(0.025)	(0.019)	(0.033)	(0.036)	(0.040)	(0.036)	(0.035)	(0.037)
Hiring	0.143***	0.140***	0.037	0.033	0.030*	0.096***	0.043	0.053	0.071**	0.029	0.050
	(0.035)	(0.036)	(0.029)	(0.025)	(0.017)	(0.028)	(0.033)	(0.036)	(0.032)	(0.032)	(0.036)
Digital	0.040	0.021	0.023	0.013	0.014	0.038	0.058*	-0.019	0.030	0.054*	-0.001
	(0.034)	(0.034)	(0.028)	(0.023)	(0.016)	(0.027)	(0.032)	(0.033)	(0.031)	(0.030)	(0.033)
Coop	0.171***	0.136***	0.105***	0.091***	0.034**	0.121***	0.060*	0.063*	0.069**	0.017	0.035
	(0.036)	(0.036)	(0.029)	(0.025)	(0.016)	(0.027)	(0.033)	(0.034)	(0.032)	(0.029)	(0.033)
Age	-0.014	0.002	-0.035***	-0.026**	-0.015**	-0.001	-0.017	0.013	-0.036**	0.055***	0.003
	(0.018)	(0.018)	(0.014)	(0.012)	(0.007)	(0.014)	(0.017)	(0.017)	(0.016)	(0.015)	(0.017)
Size	0.020	0.017	0.018**	0.016**	0.009*	0.021**	0.025**	-0.009	0.047***	0.038***	0.056***
	(0.012)	(0.012)	(0.009)	(0.008)	(0.005)	(0.009)	(0.011)	(0.012)	(0.011)	(0.010)	(0.011)
Group	0.017	0.010	0.023	-0.019	0.029*	0.004	0.019	-0.015	-0.055*	-0.015	0.032
	(0.037)	(0.037)	(0.029)	(0.024)	(0.017)	(0.028)	(0.035)	(0.036)	(0.032)	(0.032)	(0.035)
# obs.	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000

Marginal effects of Probit models (robust standard errors in parentheses). Observations weighted by a weight derived from an EB matching. All models include industry fixed-effects and a constant.
***, **, *: significant at $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

When looking at the novelty of the technology acquired by firms, RE using firms more often acquire entirely new technology or improved technology, while no statistically significant coefficient is found when the same state of technology as the one already used in the firm is purchased. This result indicates that RE is an approach used to acquire new knowledge, and linked to a certain level of technological capacity and advancement, which is in line with the finding of a strong link between in-house R&D and RE use.

Many other channels of knowledge acquisition are less closely related to innovation output compared to RE. This is particularly true for knowledge obtained from trade fairs, standardization documents and digital sources such as social media. The strongest link between knowledge acquisition and innovation is found for cooperation agreements and product innovation. Information obtained from patent files and hiring of staff from other firms are another important knowledge sources for both product and process innovation. Publications (trade journals, scientific articles) are only linked to process innovation that are not targeted at cost reduction (e.g., organizational changes or new marketing methods). For acquiring technology that is entirely new or improved compared to the existing technology in the firm, RE turns out to be a highly effective approach vis-à-vis other knowledge sources. RE seems to enable firms to learn about technology they have not been familiar with yet. Only for hiring of staff, a similarly strong relation to acquiring entirely new technology can be established. For acquiring improved technology, trade fairs and publications are similarly relevant as RE is.

When differentiating the analysis by manufacturing and services (see Table 10 and Table 11 in the Appendix), some notable differences emerge. For manufacturing, the results for product and process innovation are very similar to those for all sectors, with slightly higher marginal effects. However, the strong link between RE and the acquisition of equipment that is technologically new or improved for the firm vanishes. This link is significant for services, however, with marginal effects being twice as high as for all sectors. It is likely that software-related RE is driving this result. At the same time, the link of RE and imitations is only weakly significant in services, and the link to cost-reducing process innovation is below the statistical level of significance, although we find a significant positive link for all types of process innovation in services.

The results of the Tobit estimations on the commercial success of product and process innovation are reported in Table 5. They confirm the findings obtained for the introduction of product and process innovation. Using RE is strongly linked to a high sales share of imitations and a high share of unit cost reduction from process innovation. Again, no statistically significant relation between RE and higher novelty levels of product innovation is found. The magnitude of the link is substantial. Firm using RE obtain 3 percentage points higher sales shares from product innovations that represent imitations, while the average sales share of imitations for all firms is 7 percent. The 1.1 percentage points higher share of cost reduction among RE using firms compares to an average of 1.5 percent across all firms.

When looking at the results for manufacturing and service firms (Table 12 in the Appendix), we find a higher contribution of RE to sales with product imitations in services. Also the marginal effect of RE for all types of product innovation is higher in services than in manufacturing. At the same time, the link between RE and market novelties that are new for a regional market is negative, showing that firms that use knowledge obtained from analyzing other firms' services do not succeed with commercializing services that are new for a regional market. We do not find such a negative link for the (few) firms that introduced new-to-world services. Cost reduction resulting from process innovation is significantly higher for RE using manufacturing firms, whereas we do not find a statistically significant contribution of RE to unit cost reduction in services, although the estimated marginal effect exceeds the one found for manufacturing. This suggest a high variance in the cost reduction results among service firms using RE.

Table 5: Reverse engineering and commercial success of innovations: results of Tobit estimations (marginal effects) using EB-based weights

	Sales share of product innovations					Share of unit cost reduction from process innovation (*Cost_s*)
	Total (*Pd_s*)	Imitation (*Imit_s*)	Market novelties			
			Total (*Mnov_*s)	Regional (*Rnov_s*)	World-first (*Wnov_s*)	
Reverse	2.998**	2.960***	0.165	0.041	0.120	1.101***
	(1.230)	(1.049)	(0.515)	(0.282)	(0.387)	(0.376)
RDint	0.343***	0.212***	0.097***	0.040***	0.055***	-0.021
	(0.085)	(0.072)	(0.023)	(0.013)	(0.015)	(0.019)
nRDint	0.661***	0.422***	0.209***	0.105**	0.058*	0.231***
	(0.165)	(0.124)	(0.074)	(0.048)	(0.032)	(0.051)
Fair	0.705	1.897	-0.776	0.207	-1.373*	0.639
	(1.580)	(1.400)	(0.860)	(0.467)	(0.728)	(0.484)
Publ	0.408	0.510	-0.304	-0.024	-0.262	0.166
	(1.642)	(1.345)	(0.790)	(0.470)	(0.560)	(0.466)
Patfile	2.854*	1.011	2.275***	0.394	1.963***	0.738
	(1.549)	(1.403)	(0.579)	(0.368)	(0.452)	(0.450)
Standard	-1.546	-0.565	-0.659	-0.233	-0.238	0.091
	(1.392)	(1.266)	(0.529)	(0.315)	(0.385)	(0.436)
Hiring	3.780***	3.447***	0.676	0.348	0.476	0.550
	(1.305)	(1.146)	(0.530)	(0.303)	(0.409)	(0.383)
Digital	1.491	1.113	0.244	0.297	-0.223	0.780**
	(1.233)	(1.080)	(0.474)	(0.279)	(0.383)	(0.354)
Coop	4.368***	2.440**	2.199***	1.008***	1.294***	1.014***
	(1.275)	(1.091)	(0.556)	(0.339)	(0.422)	(0.382)
Age	-1.642**	-1.108*	-0.524**	-0.213	-0.252	-0.337*
	(0.715)	(0.642)	(0.260)	(0.161)	(0.188)	(0.182)
Size	-0.406	-0.188	0.057	0.036	0.057	0.044
	(0.396)	(0.347)	(0.159)	(0.086)	(0.122)	(0.117)
Group	-0.130	0.012	0.526	-0.102	0.652	0.098
	(1.337)	(1.187)	(0.562)	(0.306)	(0.426)	(0.406)
# obs.	4,907	4,907	4,907	4,907	4,907	4,907

Estimated coefficients of weighted Tobit models (robust standard errors in parentheses). Observations weighted by a weight derived from an EB matching. All models include industry fixed-effects and a constant.
***, **, *: significant at p<0.01, p<0.05, p<0.1.

With respect to other knowledge sources, firms with cooperation agreements obtain significantly higher sales share both with imitations and market novelties, including products that are new to the world market. Unit cost reduction from process innovation is also positively linked to co-operation agreements, with a marginal effect of similar size as the one for RE. Using information contained in patent files is related to higher sales share with world-first innovations, while hiring staff from other firms is beneficial for higher sales share with imitations. Both results are straightforward. For other knowledge sources, no strong links to the commercial success of innovations is found. Among the other control variables, R&D expenditure are essential for the commercial success with new-to-the-world innovations, while high cost reduction from process innovation requires high investment in non-R&D innovation expenditure, including the acquisition of new equipment.

4.3 RE and innovation output: IV approach

In addition to the matching approach, we use an instrumental variable (IV) approach to tackle endogeneity, based on the Lewbel model described in Section 3.1. Estimation results of the Lewbel model are reported in Table 6 (for the introduction of innovations) and Table 7 (for the commercial success of innovations). The test statistics shown in the bottom rows are important for assessing the validity of the Lewbel instruments in terms of relevance and exogeneity. To test for the relevance of the instruments, we use the Cragg-Donald statistic, which tests whether the instruments are strong enough (or not). The critical values can be found in Stock and Yogo (2005). The Kleibergen-Paap statistic also tests for instruments that may be too weak and is robust to heteroscedasticity. If the F-values of the two statistics are high, the instruments are strong and therefore relevant. The Hansen J test checks whether the instruments are truly exogenous, i.e. independent of the residuals of the second-stage estimation, and thus meeting the overidentification assumptions. The null hypothesis is that the overidentification assumptions are valid. This would not be the case for low P-values. All our estimations fulfill both the conditions of relevance and exogeneity.

Table 6: Reverse engineering and introduction of innovations: results of IV estimations based on the Lewbel model

	Product innovation					Process innovation			Acquisition of Technology		
	Total	Imitation		Market novelty		Total (*Pc*)	Cost	Other	Entirely	Improved	Same
	(*Pd*)	(*Imit*)	Total	Regional	World-first		reduction	(*Othpc*)	New	(*Techimp*)	(*Techsam*)
			(*Mnov*)	(*Rnov*)	(*Wnov*)		(*Cost*)		(*Technew*)		
Reverse	0.039	0.068*	0.032	0.009	0.026	0.052*	0.108***	-0.056	0.096**	0.052	0.082**
	(0.039)	(0.040)	(0.036)	(0.033)	(0.029)	(0.030)	(0.041)	(0.041)	(0.038)	(0.034)	(0.040)
RDint	0.009***	0.006***	0.007***	0.004***	0.005***	0.003***	-0.001	0.004***	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
nRDint	0.019***	0.014***	0.011***	0.009***	0.006***	0.021***	0.014***	0.007***	0.010***	0.013***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fair	0.067***	0.060***	0.024**	0.026***	0.002	0.104***	0.024*	0.081***	0.039***	0.108***	0.004
	(0.016)	(0.016)	(0.010)	(0.009)	(0.006)	(0.018)	(0.013)	(0.018)	(0.013)	(0.018)	(0.016)
Publ	0.003	0.005	-0.020*	-0.010	-0.017***	0.052***	0.022*	0.030*	0.005	0.142***	0.063***
	(0.016)	(0.017)	(0.010)	(0.010)	(0.007)	(0.018)	(0.013)	(0.018)	(0.013)	(0.018)	(0.016)
Patfile	0.168***	0.126***	0.203***	0.105***	0.186***	0.082***	0.077***	0.005	0.042*	-0.013	-0.006
	(0.026)	(0.028)	(0.027)	(0.024)	(0.023)	(0.023)	(0.026)	(0.029)	(0.025)	(0.024)	(0.027)
Standard	0.035*	0.035*	0.012	0.010	0.002	0.053***	0.044**	0.009	0.031*	0.064***	0.062***
	(0.019)	(0.020)	(0.015)	(0.014)	(0.011)	(0.018)	(0.018)	(0.021)	(0.017)	(0.018)	(0.019)
Hiring	0.090***	0.090***	0.021*	0.025**	-0.001	0.103***	0.053***	0.050***	0.072***	0.063***	-0.005
	(0.018)	(0.018)	(0.013)	(0.012)	(0.009)	(0.017)	(0.016)	(0.019)	(0.016)	(0.017)	(0.018)
Digital	0.113***	0.104***	0.036***	0.031***	0.012	0.126***	0.042***	0.084***	0.024*	0.056***	0.019
	(0.015)	(0.016)	(0.011)	(0.010)	(0.007)	(0.015)	(0.013)	(0.016)	(0.013)	(0.015)	(0.015)
Coop	-0.075*	-0.096**	-0.004	-0.023	0.018**	0.007	-0.028	0.035	0.032	0.057	0.027
	(0.044)	(0.044)	(0.026)	(0.026)	(0.009)	(0.046)	(0.034)	(0.045)	(0.028)	(0.041)	(0.039)
Age	-0.013*	-0.005	-0.018***	-0.013***	-0.009***	-0.030***	-0.014**	-0.016*	-0.011*	0.015*	-0.007
	(0.008)	(0.008)	(0.005)	(0.005)	(0.003)	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)	(0.008)
Size	0.011**	0.010**	0.008**	0.007**	0.006***	0.038***	0.019***	0.018***	0.030***	0.064***	0.060***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Group	0.044***	0.040**	0.022**	0.008	0.012*	0.026*	0.020	0.006	-0.017	-0.034**	-0.005
	(0.016)	(0.016)	(0.011)	(0.010)	(0.007)	(0.016)	(0.013)	(0.017)	(0.012)	(0.016)	(0.016)
Cragg-Donald F	158,288	158,288	158,288	158,288	158,288	158,288	158,288	158,288	158,288	158,288	158,288
Kleib.-Paap F	44,518	44,518	44,518	44,518	44,518	44,518	44,518	44,518	44,518	44,518	44,518
Hansen J test	0.6443	0.3926	0.2337	0.1531	0.1880	0.1122	0.9263	0.1242	0.7949	0.1598	0.6971
# obs.	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000

Marginal effects (robust standard errors in parentheses). All models include industry fixed-effects and a constant. ***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

Table 7: Reverse engineering and commercial success of innovations: results of IV estimations based on the Lewbel model

	Sales share of product innovations					Share of unit cost reduction from process innovation (*Cost_s*)
	Total (*Pd_s*)	Imitation (*Imit_s*)	Market novelties			
			Total (*Mnov_s*)	Regional (*Rnov_s*)	World-first (*Wnov_s*)	
Reverse	2.969*	3.888**	-0.919	0.229	-1.149**	1.457**
	(1.772)	(1.609)	(0.741)	(0.485)	(0.545)	(0.645)
RDint	0.557***	0.281***	0.276***	0.117***	0.158***	0.030
	(0.065)	(0.052)	(0.052)	(0.036)	(0.040)	(0.019)
nRDint	0.900***	0.466***	0.435***	0.177***	0.257***	0.200***
	(0.125)	(0.101)	(0.110)	(0.068)	(0.095)	(0.047)
Fair	1.346**	0.969*	0.377	0.344*	0.033	0.355**
	(0.642)	(0.586)	(0.283)	(0.182)	(0.220)	(0.155)
Publ	-0.211	0.285	-0.496	-0.068	-0.427	0.099
	(0.643)	(0.568)	(0.334)	(0.196)	(0.284)	(0.162)
Patfile	3.732***	1.413	2.319***	-0.005	2.325***	0.578
	(1.253)	(1.084)	(0.787)	(0.456)	(0.668)	(0.356)
Standard	0.029	0.934	-0.905**	-0.237	-0.668*	0.571**
	(0.795)	(0.735)	(0.396)	(0.225)	(0.341)	(0.267)
Hiring	2.427***	2.180***	0.248	0.036	0.211	0.519**
	(0.715)	(0.654)	(0.351)	(0.216)	(0.285)	(0.218)
Digital	3.264***	2.642***	0.622**	0.318*	0.304	0.388**
	(0.595)	(0.546)	(0.264)	(0.168)	(0.207)	(0.168)
Coop	-0.428	-0.964	0.536*	0.015	0.521***	-0.591
	(1.345)	(1.338)	(0.301)	(0.266)	(0.158)	(0.518)
Age	-1.742***	-1.111***	-0.631***	-0.303**	-0.329**	-0.392***
	(0.354)	(0.320)	(0.185)	(0.136)	(0.139)	(0.094)
Size	-0.748***	-0.515***	-0.233***	-0.103**	-0.130**	-0.062
	(0.186)	(0.171)	(0.080)	(0.046)	(0.066)	(0.051)
Group	-0.065	0.077	-0.142	-0.245	0.103	-0.036
	(0.590)	(0.539)	(0.259)	(0.161)	(0.208)	(0.165)
Cragg-Donald F	157,165	157,165	157,165	157,165	157,165	157,165
Kleib.-Paap F	41,344	41,344	41,344	41,344	41,344	41,344
Hansen J test	0.7781	0.5948	0.1053	0.4917	0.5840	0.7883
# obs.	4,907	4,907	4,907	4,907	4,907	4,907

Marginal effects (robust standard errors in parentheses). All models include industry fixed-effects and a constant.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

The IV estimation results are close to the estimation results obtained from the EB approach. This is remarkable in view of the very different methodologies and strongly supports our conclusions derived from the EB approach. The IV results confirm that RE using firms tend to produce more product imitations as well as cost-saving process innovation (see Table 6). The IV results for the link between RE and the acquisition of new or improved technology when purchasing new capital goods are somewhat different, as we find a positive effect only for entirely new technology, but not for improved technology. At the same time, RE use is also linked to acquiring new capital goods based on the same technology that a firm used before. Concerning the commercial success of innovations, we find significantly higher sales shares from product imitations and higher cost savings from process innovation, fully confirming the results obtained from the EB matching approach. For the sales share from world-first innovations, the IV estimations produce a significant negative result, which indicates that RE using firms are less focusing on world-first innovations, and that using technological knowledge from others' objects does not provide sufficient novelty to succeed with really new innovations.

4.4 Robustness checks

In order to analyze the robustness of our findings, we run a number of robustness checks. First, we use alternative measures of size, as firm size and innovation are strongly correlated (Cohen and Klepper 1996). For this purpose, we run all models by including both the absolute and the squared term of our size measure (number of full-time employees). Furthermore, we work with indicator variables for size classes (<10, 10 to 49, 50 to 249, with 250+ as reference category). The results fully correspond to those of our main estimations reported above. Secondly, we use variants in the estimation methodology. Instead of Probit, we employ linear probability models, and we use OLS instead of Tobit estimations. The results are very close to those presented above.

Thirdly, we use an alternative matching approach to correct for likely selection effects, relying on inverse probability weighting (Adabie and Catteneo 2018, Imbens and Wooldridge 2009) instead of EB weighting. For this purpose, we estimate the probability of using RE by logit models (in some cases, logit estimations do not converge, so we use linear probability models). Based on these estimation results, firms are weighted with the inverse probability of belonging to the treatment group (i.e., RE users) or the control group. The results of this matching approach correspond qualitatively exactly to those of EB matching.

Finally, we use an alternative measure for the commercial success of innovations. Instead of the sales share of product innovations, we use the logarithm of the amount of sales. For firms with no innovative sales and no cost reduction, we add the lowest observed positive value for this variable to allow for a logarithmic transformation. The estimation results based on this alternative measure correspond qualitatively to those based on the sales share both for the EB matching and the Lewbel model. All results of our robustness checks are available from the authors upon request.

5 Conclusion

This paper aimed at providing new empirical evidence on the role of reverse engineering (RE) for innovation in a high-tech economy context. Based on data from the German part of the CIS, two research questions were addressed: First, we analyzed which types of firms use RE with respect to the firms' technological capacity, business strategy, competitive environment and financial situation. Second, we investigated whether and to what extent RE contribute to innovation performance, both in terms of the novelty level of innovations and the commercial success obtained from innovation.

Our paper shows that reverse engineering is a relevant and successful approach to obtain innovation-related knowledge from other firms in the context of high-tech economies. Firms relying on RE tend to operate in a rather competitive environment and often follow a high-quality strategy. At the same time, they are stronger credit constrained compared to firms not using RE. In order to carry out RE, in-house R&D is almost a pre-requisite, confirming the critical importance of absorptive capacity to acquire external knowledge (Cohen and Levinthal 1989). The use of RE is positively linked to both product and process innovation, indicating that RE is used for a variety of purposes. RE-based product innovation tends to focus on imitation, while RE-based process innovation is closely linked to cost reduction. In addition, RE using firms are more likely to updating their technological base by acquiring new or improved technology. This result is in line with other studies that showed that knowledge spillovers from competitors tend to stimulate incremental innovation rather than more radical or novel ones (Jirjahn and Kraft 2011, Capelli et al. 2014). In the same vein, Audretsch et al. (2024) point out that cooperation with competitors (coopetition) leads to more incremental innovations.

The equal relevance of product and process innovation as an output of RE is an important finding of our study, since the existing literature often relates RE primarily to product innovation (see Levin et al. 1987). Process innovation based on RE may either result from the need to retool manufacturing facilities in order to manufacture the reverse-engineered product (Samuelson and Scotchmer 2002: 1588) or as a distinct goal of the RE activity. The latter can be illustrated by a practice case that shows that reverse engineering may focus "*on making a product easy and fast to manufacture without compromising on its performance and quality. Identifying the most efficient way to manufacture components is essential for lean manufacturing, and proves beneficial to the organization in terms of cost savings and quality control*."[2] Nathan and Sarkar (2014) also demonstrate that RE is not just about copying others products, but may also be linked to others' process innovations with the aim to reduce production costs.

The focus on process innovation of RE using firms is consistent with their competitive environment which is characterized by a high price elasticity of demand and strong international competition. Through cost reduction from process innovation, firms can gain a price advantage in the market and address their more challenging financial situation. Combined with high-quality products based on imitations of competitor products, RE can lead to a viable business strategy. Innovations based on RE often involve a change in the operating systems to be able to offer the imitated product cheaper than the original innovator. In order

[2] See the blog by Steve Park (April 21th, 2021), https://reverse-engineering-service.de/en/reverse-engineering-in-manufacturing.

to proceed with a reverse engineering strategy, the firms also need a certain amount of accumulated knowledge and in-house development capacity to effectively understand the technological solution employed by the original innovator, and to proactively imitate and modify the original product (Lee and Yoon 2015).

Another important finding of our paper is that RE is relevant both in manufacturing and services. While manufacturing firms tend to benefit from both higher sales share of product imitations and cost reduction, RE use in service firms is more strongly linked to the commercial success of imitations, while the effect on cost reduction is less pronounced.

Taking our findings together, RE use in a high-tech country context is not just an approach for 'weak' firms aiming to catch-up, but rather a distinct innovation strategy that allows firms in a challenging market environment (high price elasticity, strong competition from abroad, credit constraints) to succeed with innovation and to follow a quality-based business strategy. A key challenge for these firms is to develop and maintain a strong technological capacity required for carrying out RE processes, i.e. to identify, understand and re-produce the technological features of others' objects. There are rather few firms in a high-tech economy that follow this approach (in the case of Germany, about 7 percent), indicating that it is rather a niche approach to innovation that responds to a specific firm environment.

Our study also has limitations. The question on RE use is available for one survey year only. As a result of this cross-sectional nature of the data, we are not able to test the impact of changes e.g. in a difference-in-differences setting or through instrumental variable techniques. For this reason, our results can be interpreted as correlations and links, but not as causal impacts of RE on innovation. In addition, our RE measure is a simple binary variable which does not provide any information on the actual purpose of the RE use or on the objects that were subject to RE. This clearly limits the depth of analysis. We leave it to future research to address these issues.

6 References

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7 Appendix

Table 8: Descriptive statistics of model variables for RE using firms, manufacturing and services

	Reverse=1		Manufacturing		Services	
Variable	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Model [1]						
Reverse	1.000	0.000	0.084	0.277	0.047	0.211
RD_con	0.445	0.498	0.286	0.452	0.173	0.378
RD_occ	0.198	0.399	0.138	0.345	0.100	0.300
Patuse	0.270	0.444	0.212	0.409	0.075	0.264
HC	0.257	0.265	0.169	0.206	0.345	0.339
BS_qual	0.962	0.192	0.919	0.272	0.883	0.322
BS_newc	0.705	0.457	0.638	0.481	0.580	0.494
BS_broad	0.458	0.499	0.393	0.489	0.437	0.496
ME_entr	0.519	0.500	0.463	0.499	0.479	0.500
ME_subs	0.613	0.488	0.516	0.500	0.407	0.491
ME_elas	0.636	0.482	0.587	0.492	0.553	0.497
ME_dyn	0.527	0.500	0.403	0.491	0.482	0.500
ME_unct	0.753	0.432	0.722	0.448	0.668	0.471
ME_abr	0.517	0.500	0.438	0.496	0.226	0.418
Credsal	0.012	0.010	0.014	0.013	0.017	0.018
Credrat	3.755	0.487	3.756	0.458	3.613	0.454
Credcon	0.252	0.435	0.200	0.400	0.173	0.379
Age	3.197	0.926	3.221	0.851	2.987	0.837
Size	3.944	1.908	3.449	1.573	2.853	1.545
Group	0.463	0.499	0.332	0.471	0.252	0.434
Model [2]						
Pd	0.634	0.483	0.389	0.488	0.373	0.484
Imit	0.601	0.490	0.353	0.478	0.345	0.475
Mnov	0.258	0.438	0.144	0.351	0.086	0.281
Rnov	0.190	0.393	0.102	0.302	0.073	0.261
Wnov	0.134	0.341	0.077	0.267	0.027	0.162
Pc	0.788	0.410	0.579	0.494	0.531	0.499
Cost	0.359	0.481	0.200	0.400	0.128	0.334
Othpc	0.428	0.496	0.379	0.485	0.403	0.491
Technew	0.330	0.471	0.196	0.397	0.129	0.335
Techimpr	0.765	0.425	0.621	0.485	0.522	0.500
Techsame	0.382	0.487	0.312	0.463	0.237	0.426
Pd_s	16.438	24.490	8.337	17.179	9.071	19.690
Imit_s	13.174	21.095	6.544	14.519	7.409	17.120
Mnov_s	3.263	10.993	1.793	8.086	1.662	9.104
Rnov_s	1.553	6.358	0.717	3.628	1.089	6.901
Wnov_s	1.711	8.807	1.076	7.040	0.573	5.685
Cost_s	3.574	8.138	1.545	4.521	1.378	5.252
RDint	4.654	0.116	2.756	7.683	2.162	7.746
nRDint	1.626	9.091	1.092	3.464	0.825	3.019
Fair	0.850	0.358	0.712	0.453	0.570	0.495
Publ	0.870	0.337	0.697	0.459	0.654	0.476
Patfile	0.290	0.455	0.153	0.360	0.043	0.202
Standard	0.345	0.476	0.188	0.390	0.159	0.365
Hiring	0.478	0.500	0.227	0.419	0.208	0.406
Digit	0.563	0.497	0.305	0.461	0.386	0.487
Coop	0.478	0.500	0.293	0.455	0.249	0.433

Table 9: Entropy balancing: results before and after weighting for matching variables

	Reverse=1			*Reverse*=0					
				Before matching			After matching		
Matching variable	M	V	S	M	V	S	M	V	S
RD_con	0.445	0.248	0.220	0.217	0.170	1.371	0.446	0.247	0.220
RD_occ	0.199	0.160	1.512	0.114	0.101	2.426	0.199	0.159	1.508
BS_qual	0.962	0.037	-4.821	0.897	0.092	-2.618	0.962	0.037	-4.808
ME_elas	0.613	0.238	-0.465	0.453	0.248	0.188	0.613	0.237	-0.462
ME_dyn	0.527	0.250	-0.107	0.435	0.246	0.264	0.527	0.249	-0.106
ME_abr	0.517	0.250	-0.066	0.324	0.219	0.751	0.516	0.250	-0.065
Credsal	0.012	0.000	2.613	0.016	0.000	3.647	0.012	0.000	2.804
Credcon	0.252	0.189	1.143	0.183	0.149	1.642	0.253	0.189	1.139
Age	3.197	0.858	-0.696	3.104	0.714	-0.634	3.196	0.858	-0.692
Size	3.944	3.642	0.722	3.110	2.396	0.683	3.942	3.642	0.724
Group	0.463	0.249	0.148	0.282	0.203	0.968	0.463	0.249	0.148
Industries:									
Food/beverages	0.041	0.039	4.648	0.039	0.038	4.752	0.041	0.039	4.644
Textiles/clothing	0.051	0.048	4.087	0.023	0.023	6.323	0.051	0.048	4.084
Wood/paper	0.041	0.039	4.648	0.034	0.033	5.104	0.041	0.039	4.644
Chemicals	0.051	0.048	4.087	0.026	0.025	5.937	0.051	0.048	4.084
Plastic/non-metal prod.	0.038	0.037	4.821	0.026	0.025	5.959	0.038	0.037	4.817
Basic metals	0.038	0.037	4.821	0.030	0.030	5.461	0.038	0.037	4.817
Metal products	0.074	0.069	3.261	0.067	0.062	3.477	0.074	0.068	3.258
Electroniks	0.076	0.071	3.191	0.062	0.058	3.636	0.076	0.071	3.189
Machinery	0.109	0.098	2.502	0.040	0.038	4.715	0.110	0.098	2.498
Vehicles	0.033	0.032	5.222	0.017	0.017	7.482	0.033	0.032	5.218
Other manufacturing	0.059	0.055	3.762	0.054	0.051	3.941	0.059	0.055	3.759
Utilities	0.015	0.015	7.907	0.030	0.029	5.552	0.015	0.015	7.900
Waste management	0.023	0.022	6.379	0.044	0.042	4.435	0.023	0.022	6.372
Construction	0.008	0.008	11.310	0.025	0.024	6.074	0.008	0.008	11.280
Wholesale	0.036	0.034	5.011	0.042	0.040	4.575	0.036	0.034	5.007
Transport	0.033	0.032	5.222	0.062	0.058	3.624	0.033	0.032	5.216
Media	0.033	0.032	5.222	0.041	0.039	4.644	0.033	0.032	5.217
IT services	0.061	0.057	3.666	0.055	0.052	3.902	0.061	0.057	3.663
Financial services	0.023	0.022	6.379	0.028	0.027	5.746	0.023	0.022	6.372
Engineer./R&D serv.	0.061	0.057	3.666	0.089	0.081	2.880	0.061	0.057	3.663
Consulting services	0.025	0.025	6.027	0.060	0.057	3.689	0.026	0.025	6.018
Other business serv.	0.053	0.051	3.971	0.079	0.073	3.116	0.054	0.051	3.968

M: mean, V: variance, S: skewness

Table 10: Reverse engineering and introduction of innovations in manufacturing: results of Probit estimations (marginal effects) using EB-based weights

	Product innovation					Process innovation			Acquisition of Technology		
	Total (*Pd*)	Imitation (*Imit*)	Market novelty Total (*Mnov*)	Market novelty Regional (*Rnov*)	Market novelty World-first (*Wnov*)	Total (*Pc*)	Cost reduction (*Cost*)	Other (*Othpc*)	Entirely New (*Technew*)	Improved (*Techimp*)	Same (*Techsam*)
Reverse	0.073*	0.105***	0.051	0.042	-0.003	0.005	0.105***	-0.112***	0.033	0.036	0.058
	(0.040)	(0.040)	(0.036)	(0.030)	(0.020)	(0.032)	(0.039)	(0.038)	(0.037)	(0.033)	(0.039)
RDint	0.001	0.001	0.001	0.001	0.001	-0.002	-0.004**	0.003	0.002	-0.003	0.001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
nRDint	0.016**	0.018***	0.007	0.005	0.003	0.021***	0.016***	-0.001	0.011**	0.012**	-0.002
	(0.007)	(0.007)	(0.005)	(0.004)	(0.002)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Fair	-0.078	-0.054	0.048	0.023	0.024	0.055	-0.012	0.112**	0.013	0.121**	0.065
	(0.049)	(0.056)	(0.050)	(0.045)	(0.030)	(0.044)	(0.059)	(0.051)	(0.059)	(0.060)	(0.059)
Publ	0.018	0.006	-0.072	-0.047	-0.118**	0.189***	0.020	0.192***	0.057	0.093*	0.077
	(0.053)	(0.055)	(0.057)	(0.050)	(0.048)	(0.053)	(0.054)	(0.042)	(0.052)	(0.051)	(0.054)
Patfile	0.172***	0.111**	0.161***	0.073*	0.098***	0.090**	0.093*	-0.017	0.033	0.061	-0.049
	(0.051)	(0.054)	(0.049)	(0.040)	(0.032)	(0.041)	(0.052)	(0.052)	(0.049)	(0.041)	(0.052)
Standard	-0.044	-0.028	-0.023	-0.054*	0.035	-0.024	-0.031	0.006	0.043	-0.000	0.094*
	(0.056)	(0.054)	(0.043)	(0.033)	(0.026)	(0.042)	(0.047)	(0.049)	(0.046)	(0.043)	(0.049)
Hiring	0.128***	0.129***	0.028	0.020	0.048**	0.076**	0.065	0.010	0.061	-0.004	0.057
	(0.043)	(0.044)	(0.039)	(0.033)	(0.024)	(0.034)	(0.043)	(0.043)	(0.039)	(0.038)	(0.045)
Digital	0.011	-0.001	0.013	0.011	0.014	0.001	0.055	-0.062	-0.001	0.022	-0.020
	(0.043)	(0.043)	(0.038)	(0.031)	(0.023)	(0.033)	(0.041)	(0.039)	(0.039)	(0.035)	(0.042)
Coop	0.153***	0.128***	0.121***	0.104***	0.044*	0.110***	0.024	0.089**	0.066*	0.016	0.006
	(0.044)	(0.044)	(0.038)	(0.032)	(0.023)	(0.033)	(0.043)	(0.041)	(0.039)	(0.034)	(0.043)
Age	-0.030	-0.011	-0.043**	-0.034**	-0.017*	-0.011	0.005	-0.019	-0.036*	0.054***	-0.015
	(0.022)	(0.023)	(0.019)	(0.017)	(0.010)	(0.017)	(0.023)	(0.022)	(0.020)	(0.018)	(0.022)
Size	0.020	0.013	0.024*	0.018*	0.018**	0.031**	0.017	0.010	0.046***	0.053***	0.062***
	(0.016)	(0.016)	(0.012)	(0.011)	(0.007)	(0.013)	(0.015)	(0.016)	(0.013)	(0.013)	(0.015)
Group	0.052	0.055	0.045	-0.010	0.031	0.001	0.015	-0.016	-0.044	-0.025	0.021
	(0.045)	(0.046)	(0.040)	(0.034)	(0.024)	(0.035)	(0.044)	(0.044)	(0.039)	(0.038)	(0.046)
# obs.	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591

Marginal effects of Probit models with robust standard errors (standard errors in parentheses). Observations weighted by a weight derived from an entropy balancing (EB) matching. All models include industry fixed-effects. ***, **, *: significant at p<0.01, p<0.05, p<0.1.

Table 11: Reverse engineering and introduction of innovations in services: results of Probit estimations (marginal effects) using EB-based weights

	Product innovation					Process innovation			Acquisition of Technology		
	Total (*Pd*)	Imitation (*Imit*)	Market novelty Total (*Mnov*)	Market novelty Regional (*Rnov*)	Market novelty World-first (*Wnov*)	Total (*Pc*)	Cost reduction (*Cost*)	Other (*Othpc*)	Entirely New (*Technew*)	Improved (*Techimp*)	Same (*Techsam*)
Reverse	0.068	0.092*	-0.021	-0.021	0.006	0.090**	0.058	0.015	0.138***	0.111**	0.002
	(0.054)	(0.053)	(0.030)	(0.027)	(0.008)	(0.041)	(0.045)	(0.054)	(0.048)	(0.049)	(0.047)
RDint	0.014***	0.008***	0.006***	0.004***	0.001**	-0.002	-0.002	0.001	-0.000	-0.001	-0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
nRDint	0.052***	0.025***	0.007**	0.006**	0.000	0.023***	0.011**	-0.002	0.005	0.002	-0.008
	(0.011)	(0.006)	(0.003)	(0.003)	(0.000)	(0.007)	(0.005)	(0.008)	(0.006)	(0.007)	(0.005)
Fair	0.072	0.127*	-0.034	-0.005	-0.016	0.069	0.074	0.012	0.087	0.064	-0.009
	(0.065)	(0.070)	(0.042)	(0.038)	(0.013)	(0.050)	(0.046)	(0.064)	(0.053)	(0.063)	(0.057)
Publ	-0.089	-0.113*	0.023	0.030	-0.001	0.001	0.001	0.053	-0.012	0.098	0.007
	(0.063)	(0.065)	(0.033)	(0.029)	(0.008)	(0.043)	(0.053)	(0.064)	(0.069)	(0.063)	(0.062)
Patfile	0.064	-0.005	0.180**	0.019	0.067**	0.090	0.150	-0.047	0.053	-0.032	-0.030
	(0.106)	(0.108)	(0.085)	(0.057)	(0.032)	(0.069)	(0.101)	(0.101)	(0.089)	(0.100)	(0.073)
Standard	0.030	0.080	-0.024	0.010	0.000	0.044	0.031	-0.009	0.057	0.097*	0.013
	(0.063)	(0.065)	(0.034)	(0.032)	(0.007)	(0.049)	(0.050)	(0.066)	(0.056)	(0.058)	(0.052)
Hiring	0.189***	0.176***	0.074**	0.069**	0.001	0.114***	0.013	0.102*	0.080	0.079	0.025
	(0.057)	(0.058)	(0.036)	(0.032)	(0.008)	(0.044)	(0.045)	(0.059)	(0.053)	(0.058)	(0.053)
Digital	0.081	0.066	0.027	0.007	0.005	0.122***	0.061	0.070	0.081*	0.116**	0.035
	(0.056)	(0.056)	(0.031)	(0.029)	(0.009)	(0.045)	(0.045)	(0.057)	(0.049)	(0.055)	(0.048)
Coop	0.203***	0.162***	0.067**	0.056*	0.007	0.145***	0.150***	0.006	0.079	0.018	0.082*
	(0.056)	(0.059)	(0.032)	(0.030)	(0.007)	(0.044)	(0.051)	(0.059)	(0.052)	(0.055)	(0.048)
Age	0.007	0.014	-0.018	-0.010	-0.001	0.011	-0.054**	0.066**	-0.040	0.055**	0.029
	(0.027)	(0.027)	(0.015)	(0.015)	(0.002)	(0.024)	(0.023)	(0.029)	(0.024)	(0.027)	(0.027)
Size	0.020	0.023	0.010	0.013	-0.003	0.007	0.036**	-0.037**	0.051***	0.015	0.045***
	(0.017)	(0.018)	(0.010)	(0.008)	(0.002)	(0.013)	(0.014)	(0.018)	(0.016)	(0.015)	(0.015)
Group	-0.065	-0.088	-0.024	-0.041	0.012	-0.008	0.028	-0.039	-0.090*	-0.022	0.052
	(0.059)	(0.060)	(0.030)	(0.027)	(0.008)	(0.042)	(0.050)	(0.060)	(0.048)	(0.054)	(0.049)
# obs.	2,409	2,409	2,409	2,409	2,099	2,409	2,409	2,409	2,409	2,409	2,409

Marginal effects of Probit models with robust standard errors (standard errors in parentheses). Observations weighted by a weight derived from an entropy balancing (EB) matching. All models include industry fixed-effects. ***, **, *: significant at p<0.01, p<0.05, p<0.1.

Table 12: Reverse engineering and commercial success of innovations in manufacturing and services: results of Tobit estimations using EB-based weights

	Sales share of product innovations										Share of unit cost reduction from process innovation (*Cost_s*)	
	Total (*Pd_s*)		Imitation (*Imit_s*)		Market novelties							
					Total (*Mnov_s*)		Regional (*Rnov_s*)		World-first (*Wnov_s*)			
	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services
Reverse	2.385*	4.372**	2.848**	3.385**	0.070	-0.487	0.170	-0.975**	-0.198	0.738	0.951**	1.271
	(1.407)	(2.069)	(1.225)	(1.723)	(0.484)	(1.027)	(0.272)	(0.486)	(0.351)	(0.949)	(0.396)	(0.797)
RDint	0.118	0.660***	0.026	0.444***	0.063**	0.178***	0.022*	0.087***	0.037**	0.089***	-0.036*	0.006
	(0.085)	(0.105)	(0.065)	(0.108)	(0.027)	(0.040)	(0.013)	(0.025)	(0.018)	(0.032)	(0.022)	(0.033)
nRDint	0.656***	0.646***	0.547***	0.231	0.121**	0.339***	0.031	0.213**	0.068*	0.080	0.244***	0.176**
	(0.202)	(0.233)	(0.168)	(0.155)	(0.058)	(0.120)	(0.028)	(0.085)	(0.039)	(0.052)	(0.071)	(0.068)
Fair	-2.698	3.983**	-1.175	5.140***	-0.674	-1.933	0.281	-0.585	-1.215	-1.897	-0.237	1.793**
	(2.140)	(1.954)	(1.823)	(1.925)	(1.033)	(1.272)	(0.429)	(0.746)	(0.881)	(1.154)	(0.599)	(0.763)
Publ	0.539	0.269	1.115	-0.584	-0.796	1.343	-0.011	0.487	-0.833	0.837	0.260	-0.164
	(2.093)	(2.079)	(1.783)	(1.662)	(0.846)	(1.321)	(0.395)	(0.778)	(0.664)	(0.848)	(0.537)	(0.791)
Patfile	4.802***	-0.206	3.038**	-2.476	1.846***	3.236***	0.120	1.521*	1.706***	2.398***	0.827*	1.023
	(1.663)	(3.150)	(1.500)	(2.930)	(0.619)	(1.125)	(0.329)	(0.844)	(0.531)	(0.708)	(0.462)	(1.074)
Standard	-3.757**	2.279	-2.712*	3.396	-0.632	-0.993	-0.233	-0.479	-0.109	-0.600	-0.345	0.997
	(1.647)	(2.130)	(1.434)	(2.115)	(0.577)	(0.959)	(0.312)	(0.639)	(0.425)	(0.630)	(0.495)	(0.780)
Hiring	4.021**	3.866*	3.412**	3.567*	0.529	2.123**	0.022	1.686***	0.653	0.397	0.793*	0.104
	(1.588)	(2.029)	(1.370)	(1.866)	(0.586)	(0.879)	(0.288)	(0.574)	(0.465)	(0.654)	(0.419)	(0.773)
Digital	1.263	2.517	0.837	2.276	0.251	0.167	0.042	1.137*	0.026	-1.007	0.741*	0.958
	(1.474)	(1.896)	(1.298)	(1.607)	(0.472)	(0.991)	(0.269)	(0.610)	(0.369)	(0.863)	(0.400)	(0.724)
Coop	4.127***	5.481***	2.022*	4.026**	2.337***	1.611*	0.874***	0.924*	1.562***	0.371	0.709*	2.068***
	(1.470)	(2.065)	(1.221)	(2.001)	(0.614)	(0.879)	(0.320)	(0.556)	(0.524)	(0.646)	(0.425)	(0.723)
Age	-0.821	-2.998***	-0.578	-2.178**	-0.327	-0.711	-0.152	-0.167	-0.098	-0.410	-0.127	-0.745**
	(0.847)	(1.045)	(0.763)	(0.937)	(0.244)	(0.518)	(0.152)	(0.289)	(0.175)	(0.381)	(0.193)	(0.367)
Size	-0.907*	0.387	-0.516	0.295	-0.061	0.402	0.003	0.242	0.013	0.117	-0.099	0.308
	(0.495)	(0.516)	(0.408)	(0.484)	(0.162)	(0.325)	(0.091)	(0.168)	(0.114)	(0.230)	(0.145)	(0.188)
Group	2.099	-4.479**	1.787	-3.488*	0.837	-0.721	0.058	-0.946	0.680	0.567	0.211	-0.015
	(1.562)	(2.156)	(1.313)	(2.029)	(0.621)	(1.124)	(0.291)	(0.600)	(0.496)	(0.705)	(0.421)	(0.788)
# obs.	2,538	2,369	2,538	2,369	2,538	2,369	2,538	2,369	2,538	2,369	2,538	2,369

Estimated coefficients of weighted Tobit models with robust standard errors (standard errors in parentheses). Observations weighted by a weight derived from an entropy balancing (EB) matching. All models include industry fixed-effects. ***, **, *: significant at p<0.01, p<0.05, p<0.1.

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