# Employee characteristics, absorptive capacity and innovation

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# Employee Characteristics, Absorptive Capacity and Innovation*

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**Abstract**

We investigate the determinants of firm absorptive capacity, with a particular focus on the effect of employee characteristics, and study how it affects a firm's ability to generate new knowledge. Using administrative and national survey data on individuals and businesses, we first estimate absorptive capacity measures for New Zealand firms. We then show that the share of employees with international experience and the average skill level of employees have a positive impact on a firm's learning capabilities, and that the positive effect of employees with international experience is greater if the firm also has a highly skilled workforce overall. We finally find that a firm's absorptive capacity is highly positively correlated to the likelihood of the firm innovating.

***Keywords***— Absorptive capacity, knowledge spillover, innovation, linked employer-employee data

***JEL codes***— D20, D22, D24, O31

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*Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. The results presented in this study are the work of the authors, not Stats NZ or individual data suppliers. These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) and Longitudinal Business Database (LBD) which are carefully managed by Stats NZ. For more information about the IDI and LBD please visit https://www.stats.govt.nz/integrated-data/. The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

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# 1 Introduction

Knowledge is essential to a firm's innovation process. A firm that is developing a new product seeks information from different sources. It may collect feedback from customers on the desired features in a product, or it may have its employees with relevant knowledge attend industry conferences to gather information pertinent to the firm's technical capabilities to manufacture a new product. Obtaining valuable information is seldom costless, firms need to invest effort into exploiting knowledge spillovers.

Cohen and Levinthal (1989, 1990) suggest that a firm's R&D efforts contribute to its absorptive capacity, defined as the ability to recognise, assimilate and apply relevant information from external sources to generate new knowledge. This study contributes to the existing literature on absorptive capacity by using individual level employee data linked to firm level innovation data in Statistics New Zealand's integrated data infrastructure (IDI) to examine the role of employee characteristics in explaining firm absorptive capacity, that is, the firms' efforts to obtain beneficial information from external sources and utilise it to support their own pursuit for new knowledge.

The underlying premise of the concept of absorptive capacity is that prior related knowledge is required to learn and apply new knowledge. At an individual level, prior knowledge enables an associative learning process where an individual retains new information by creating connections to knowledge stored in memory. This also extends to the undertaking of learning itself: an individual that has experienced learning a task can subsequently apply the skills to learning more tasks. Similarly, applying newly acquired knowledge to innovate builds on transferring skills from previous experience of carrying out such tasks.

A firm's absorptive capacity depends on the absorptive capacity of its employees, but it is distinctive in that the firm is required to consider the knowledge transfer not only from external sources but also across and within its units and employees. Therefore, a firm may trade off developing efficiency of internal communication against the ability of collecting and using information from external sources. A balance between sufficient common knowledge shared across individuals to ensure efficient communication and still possessing the diversity to help utilise various sources of information is required. Li (2016) also develops on the importance of knowledge sharing in growth of firms and shows that a costly process of sharing knowledge among employees in a rapidly growing firm results in fragmentation of knowledge and loss of early knowledge. A resulting optimal decision for a firm is to choose to slow down growth in order to ensure diffusion of knowledge and higher productivity in subsequent periods.

We approach our analysis in three steps. We start by measuring the firms' unobserved absorptive capacity. Following Murovec and Prodan (2009) and Harris and Le (2018), we identify firms that responded to a national survey on innovation (Business

Operations Survey) to measure absorptive capacity using the structural equation modelling (SEM) method, specifying a two-factor model of demand-pull and science-push absorptive capacity. We then regress the demand-pull and science-push absorptive capacity indices obtained from the SEM on control variables indicating employee characteristics, firm dynamics and market conditions in an ordered probit model to evaluate their effects. Finally, we estimate the relationship between absorptive capacity and innovation by fitting a logit model on the likelihood of firms innovating.

We find that both, demand-pull and science-push absorptive capacity levels are highly skewed to the right. Both types are higher in previously innovating firms, but the difference to non-innovating firms is much higher for demand-pull than science push absorptive capacity.

Next, we find that, statistically, both types of absorptive capacity are significantly impacted by the workers' and the managers' international experience and skills. There is evidence of complementarity of worker skills and workers' international experience: the probability of the firm's absorptive capacity being in the highest quartile is the greatest when both the share of employees with international experience and average worker skills are high. As in the previous literature, having new organizational or management practices, having previously engaged in R&D, and being an exporter both statistically and economically significantly increase a firm's absorptive capacities.

We model current innovation as a non-linear function of the two types of absorptive capacity. Doing so, we find that both types of absorptive capacity significantly increase a firm's propensity to innovate in the current period, albeit at a decreasing rate. In contrast, Murovec and Prodan (2009) use a linear specification and find that science-push absorptive capacity has a negative impact on innovation. Our findings suggest that the probability to innovate starts to decrease with an increase in the absorptive capacities when their levels are well into their 90th percentile. In our sample of New Zealand firms, a unit-increase of demand-pull absorptive capacity increases the probability of a firm innovating by more (by a large margin) than a unit-increase of science-push absorptive capacity. This relative size comparison is in line with the findings in Murovec and Prodan (2009) for firms in Spain and the Czech Republic. Measures of lagged innovation significantly and positively impact current innovation, however, lagged R&D expenditures do not. This suggests that previous R&D expenditures impact current innovation through absorptive capacity only. Similarly, lagged employee characteristics only seem to impact innovation via absorptive capacity.

We control for various variables indicating hindrances to innovating, none of which impacts innovation at conventional levels of statistical significance. We employ two different sets of variables to control for the firms' competitive environment: A quadratic formulation of the firms' profit margins and dummy variables indicating the number of competitors the firm reports and whether any of them is dominant. Whereas profit margins do not significantly impact the probability to innovate, the set of dummy variables shows a positive impact of competition: New Zealand firms seem to innovate predominantly to escape their competition.

## 2 Literature

Our study is closely aligned to existing literature which uses structural equation modelling (SEM) method to measure absorptive capacity (Harris & Le, 2018; Murovec & Prodan, 2009). The SEM combines factor analysis to find a latent variable, in this case absorptive capacity, using observed measurement variables, and linear regression to investigate determinants of absorptive capacity and the effect on innovation outcome. The advantage of using the SEM method is that it permits absorptive capacity to be distinguished from R&D, which, in turn, allows to consider R&D as a separate variable in examining determinants of absorptive capacity, as well as to estimate the influence of R&D and absorptive capacity on innovation. This distinction is not possible in studies which use variables such as R&D expenditure (Cohen & Levinthal, 1990) or citations (Mancusi, 2008) as proxies of absorptive capacity.

We estimate a two-factor measurement model of demand-pull and science-push absorptive capacity, as suggested by Murovec and Prodan (2009). A one-sided view of innovation is deemed as insufficient in measuring absorptive capacity, stemming from the long-standing debate in studies of innovation. The science-push argument says that scientific and technological progress determines the rate of innovation. As science advances, new lines of research and products are developed, therefore "pushing" firms to innovate and benefit as the first mover. Other firms in turn look to innovate in order to stay in the market, or face, as Schumpeter (1934) puts, a "competitive elimination". On the other hand, the demand-pull argument suggests that market conditions create incentives for firms to invest in innovation. In this case, innovation is a reactive phenomenon, in response to market demand (Nemet, 2009). Similarly, Schweisfurth and Raasch (2018) distinguish between "need" and "solution" absorptive capacity, where the former is developed using knowledge on unmet customer needs, and the latter using knowledge on technical solutions. In further recent literature quantifying the determinants of absorptive capacity, Crescenzi and Gagliardi (2018) study the link between firm-level innovative performance and innovation prone external environments, Miguélez and Moreno (2015) explore the extent to which absorptive capacity determines knowledge flows' impact on regional innovation, and Ebers and Maurer (2014) investigate the interplay of potential and realized absorptive capacity.

We use the same data source as Harris and Le (2018). By doing so, we uncover the underlying motivations of firms for seeking information from external sources. For example, Harris and Le (2018) identify that the manufacturing sector has the highest absorptive capacity in New Zealand. Our model shows that this is mainly in response to market conditions, more so than technological opportunities. Furthermore, we investigate the relationship between individual workers and firm absorptive capacity in New Zealand by using a linked employer-employee data. Several studies have investigated the effect of employees on firm *innovation* in New Zealand, particularly in determining the role of immigrants (Maré et al., 2014; McLeod et al., 2014), but no studies have examined the effect on *absorptive capacity* prior to ours. Maré et al. (2014) do not find significant impact of worker skills on the likelihood of firm innovation once firm dynamics are controlled for, while McLeod et al. (2014) find, even when firm dynamics are controlled for, that firms with higher share of skilled workers are more likely to innovate. In light of these mixed results in the existing literature, our findings suggest that the impact of worker skills on the likelihood of a innovating is not statistically significant once absorptive capacity is taken into account in the model specification. Internationally, Vinding (2006) and Lopez-Garcia and Montero (2012) use linked data set to examine the role of employees on firm absorptive capacity in Denmark and Spain, respectively. Both studies find that variables related to human capital are significantly associated with firm absorptive capacity.

# 3 Theoretical background

We base our empirical model associating the role of employees to firm absorptive capacity on the general theoretical model specified in Leahy and Neary (2007), a simplified version of which we present in Appendix A. We apply the implications of the model more broadly and interpret R&D as the stock of knowledge, or prior knowledge, accumulated through engaging in activities not confined to just R&D but extended to include others such as exchanging information with other relevant agents, for example, by attending industry workshops. The usable rival R&D can be viewed as information that is available, but obtaining this information is not costless, a firm must make an effort, such as attending these workshops or developing external relationships, in order to share information. This requirement of the firm having to exert its own effort to exploit spillovers from other firms' efforts implies that "there is no manna from heaven", as Kamien and Zang (2000) have described.

Furthermore, we characterise the exogenous parameter capturing a firm's difficulty of absorbing usable rival R&D as the firm's 'capabilities'. For a given level of complexity of knowledge spillovers, the effectiveness of the firm's own stock of knowledge depends on whether the firm is capable of appreciating the intricacies of the incoming knowledge. In this interpretation of the model, a highly capable firm may put in the same amount of effort as another firm of lesser capability and yield greater benefit from spillovers. We empirically examine these theoretical implications as well as empirical evidence in the literature, using data on firms' participation in activities that manifest as the firms' effort to invest in exploiting spillovers through benefiting from using external sources of information and the skill composition of workers to represent the firm's capabilities.

# 4 Empirical strategy

Our analysis investigates the following research questions. What are the attributes of demand-pull and science-push absorptive capacity in New Zealand firms? How do employee characteristics of a firm, particularly the international experience and skill levels of employees, affect its absorptive capacity? What is the effect of absorptive capacity on the likelihood of firms innovating? We approach these questions in three stages. An empirical examination of absorptive capacity requires foremost a way of measuring the unobserved absorptive capacity. Following Murovec and Prodan (2009) and Harris and Le (2018), we identify firms that responded to a national survey on innovation (Business Operations Survey) to measure absorptive capacity using the structural equation modelling (SEM) method, specifying a two-factor model of demand-pull and science-push absorptive capacity. We then regress the demand-pull and science-push absorptive capacity indices obtained from the SEM on control variables indicating employee characteristics, firm dynamics and market conditions in an ordered probit model to evaluate their effects. Finally, we estimate the relationship between absorptive capacity and innovation by fitting a logit model on the likelihood of firms innovating.

## 4.1 Measuring absorptive capacity

The SEM method estimates continuous latent variable using observed exogenous or endogenous variables, which can be discrete or continuous. The observed variables reflect the various aspects of the construct of the latent variables (Kline, 2011). We use constructs about a firm's external sources of knowledge and cooperative arrangements with external agents to represent two latent variables, demand-pull and science push absorptive capacity. Absorptive capacity is a factor that is not directly observable, but following the argument from Murovec and Prodan (2009), we use a set of measurement variables to reflect a commonality that distinguishes itself as absorptive capacity that arises in response to the market demand, the demand-pull absorptive capacity, compared to absorptive capacity that is determined as a result of technological or scientific advancement in the industry, the science-push absorptive capacity.

The last measurement component of the model relates the latent variable, overall absorptive capacity, to the observed variables indicating whether a firm is engaging in

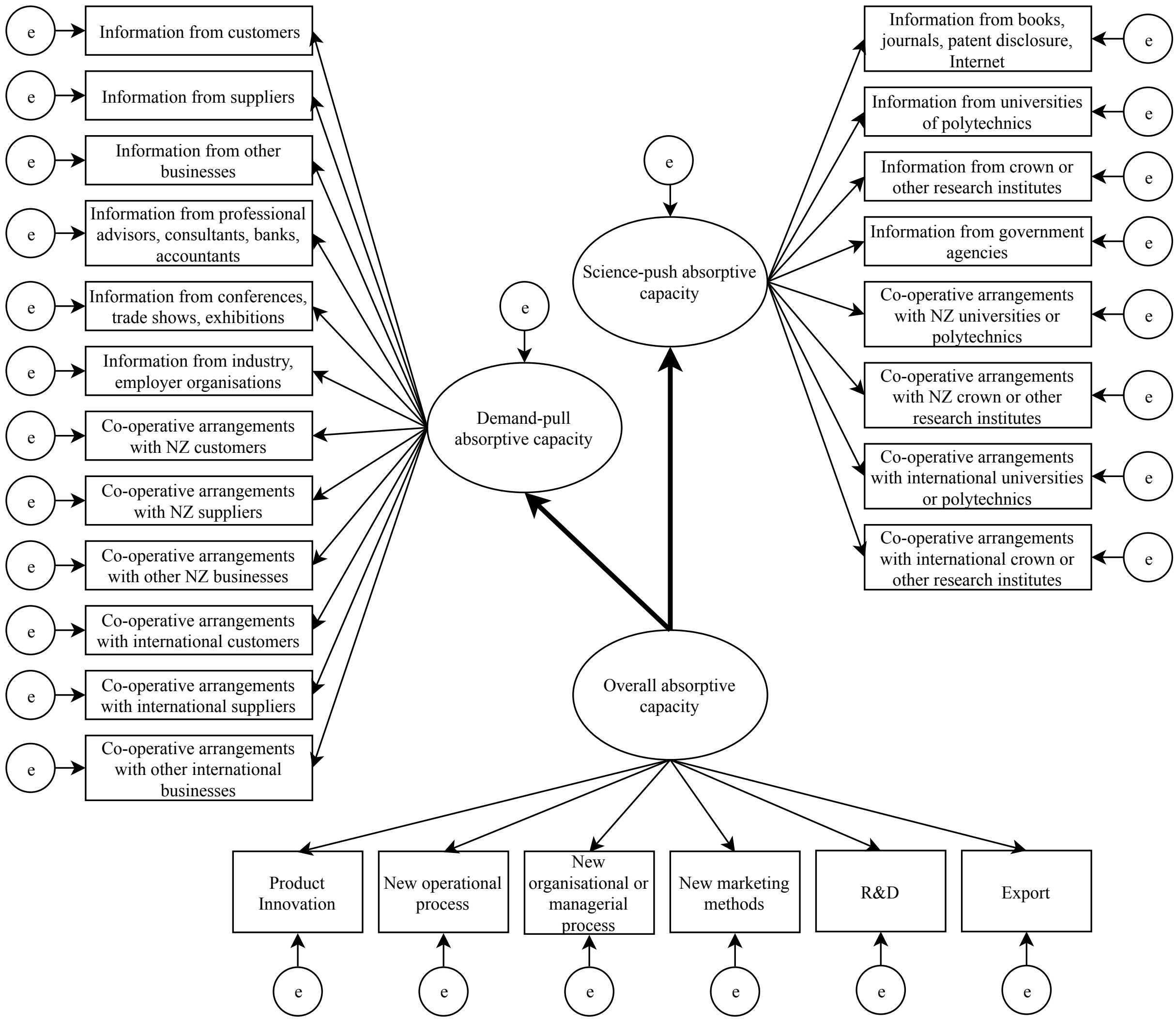



Figure 1: Structural equation model of absorptive capacity

R&D, export or performing four types of innovation. This specification largely follows Harris and Le (2018), the difference lies in including all four types of innovation as measurement variables for the overall absorptive capacity. Additionally, based on the construct of the two types of absorptive capacity, we specify in the model a structural component, in which the overall absorptive capacity is related to both demand-pull absorptive capacity and science-push absorptive capacity. This implies that demand-pull and science-push absorptive capacity co-vary through the overall absorptive capacity.

Figure 1 shows a path model of the measurement and structural components of the model. It is important to note that a SEM specification is based on the assumptions made, because essentially the model is specifying the direction of causality. The model has a total of four components: the measurement models for demand-pull absorptive capacity, science-push absorptive capacity and overall absorptive capacity, and a structural model of demand-pull, science-push and overall absorptive capacity.

To understand the model further, consider a general case for a firm in a specific point in time. Denote the latent variable demand-pull absorptive capacity as $L_d$, and the twelve measurement variables for demand-pull absorptive capacity as $x_1, x_2, ..., x_{12}$. The specification of the measurement model component corresponds to estimating the below relationship, where $\alpha$ refers to the constant term, $\beta$ refers to the coefficient associated with the latent exogenous variable $L_d$, and $e$ refers to the error term.

$$
\begin{aligned}
x_1 &= \alpha_1 + \beta_1 L_d + e_1 \\
x_2 &= \alpha_2 + \beta_2 L_d + e_2 \\
&\vdots \\
x_{12} &= \alpha_i + \beta_{12} L_d + e_{12}
\end{aligned}
$$

The measurement component estimates the linear probability of a firm using different sources of information and cooperative arrangements given a value of latent absorptive capacity value. The structural component of the SEM then implies demand-pull and science-push absorptive capacity are correlated to each other through the overall absorptive capacity. The nature of the relationship in the structural component is a correlation rather than a causal one, as it would not be sensible to suggest that overall absorptive capacity causes demand-pull and science-push absorptive capacity to increase or decrease.

## 4.2 Decomposing firm absorptive capacity

An initial OLS regression with absorptive capacity as the dependent variable and other control variables revealed a strong curvature in the residual plot versus fitted values, which persisted after log-transforming the dependent variable. As does Harris and Le (2018), we use the quartile grouping to estimate an ordered probit model, and contribute to the existing literature by running the regression on both demand-pull and science-push absorptive capacity.

The underlying linear model specification for a continuous dependent variable absorptive capacity $q^*$ for firm $j$ at time $t$ is:

$$q^*_{jt} = E_{jt-2}\beta_1 + F_{jt-2}\beta_2 + X_{jt}\beta_3 + l_r + \zeta_m + \tau_t + \varepsilon_{jt} \tag{1}$$

where $E_{jt-2}$ represents a matrix of employee characteristics for firm $j$ at lagged time period $t-2$, which includes share of employees with international experience, employee skill levels and an interaction term of the two variables, and $\beta_1$ a vector of employee characteristics coefficients. $F_{jt-2}$ is a matrix of lagged variables at $t-2$ for firm $j$, which includes past innovation, profit margin, engaging in R&D or export, and use of appropriability measures, with $\beta_2$ a vector of coefficients associated with firm level lagged variables. $X_{jt}$ represents firm level control variables at time $t$, which includes dummy variables indicating size and age of the firm, and $\beta_3$ is a vector of coefficients associated with $X_{jt}$. $l_r$ represents firm location fixed effects, $\zeta_m$ represents industry fixed effects and $\tau_t$ represents time fixed effects. Lastly, $\varepsilon_{jt}$ is a random error with a zero-mean, assumed to be distributed normally.

The quartile grouping implies that absorptive capacity is only observed through four discrete values $i = \{1,2,3,4\}$ with 4 indicating the top quartile range of absorptive capacity values in the dataset. The ordered probit model for each outcome is specified as follows:

$$\begin{aligned} Pr(q_{jt} = i) = \Phi(&\mu_i - E_{jt-2}\beta_1 - F_{jt-2}\beta_2 - X_{jt}\beta_3 - l_r - \zeta_m - \tau_t) \\ &- \Phi(\mu_{i-1} - E_{jt-2}\beta_1 - F_{jt-2}\beta_2 - X_{jt}\beta_3 - l_r - \zeta_m - \tau_t) \end{aligned} \tag{2}$$

where $\Phi$ represents the cumulative distribution function of $\varepsilon$, and taking $-\infty$ and $\infty$ for $\mu_0$ and $\mu_4$ respectively.

We consider innovation as an iterative process, and assume that having performed innovation in the previous time period contributes to accumulation of prior related knowledge required for innovation in the subsequent period. Existing studies on innovation also use lagged variables related to innovation to capture the influence of past innovation. The model, however, is not dynamic as we do not include the lagged dependent variable as an explanatory variable. We include control variables for firm size and industry in all regression model specifications in order to take into consideration the sampling methodology.[1]

Our linked employer-employee dataset includes all employees for whom the firm filed tax reports within two years of the balance date indicated by the firm, to align to the two-year period that firms take into account to indicate whether they have introduced an innovative measure anytime during this period. A worker included in the current time period may have started employment post-innovation. This introduces a potential reverse causality issue, in which a firm may choose to employ more workers as a result of innovation, and hire workers with higher skills and regard international experience more highly as a source of prior related knowledge or new ideas.

We seek to overcome the reverse causality issue by using a two-year lagged variable for employee characteristics. McLeod et al. (2014), who also derive the firm level share of migrants and New Zealand returnee from the same data source, attempt to mitigate the endogeneity by using an instrumental variables approach, one of which is the lagged variable, but note that this instrument was not highly correlated with the variable in the current period. The authors' view is that including employees within

[1]BOS adopts a two-way stratified sampling method to identify survey respondents based on firm size and industry, and these sampling weights are taken into account in official statistics.

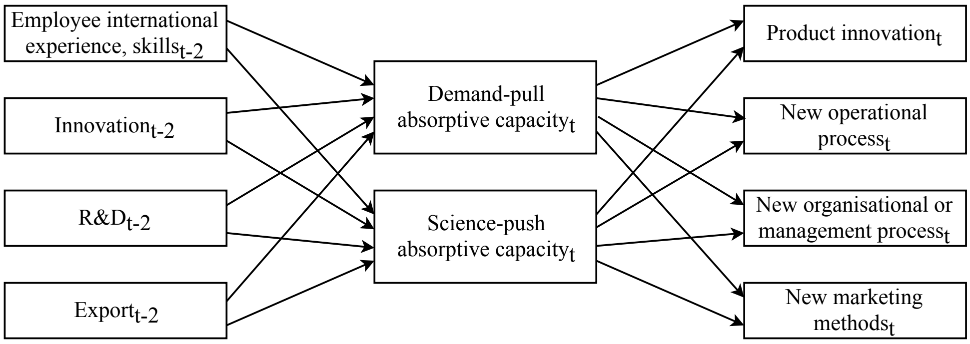



Figure 2: A conceptual diagram of the relationship between absorptive capacity and innovation

the same period as innovation enables to capture the effects of new ideas from these workers which are likely to occur within a relatively short window.

We include in the model an interaction term of share of employees with international experience and average worker skills. We posit that the beneficial influence of employees with international experience on firm absorptive capacity is accentuated if the average skill level of overall employees is also high. This is to take into account co-workers of those with international experience, that the higher average worker skill at firm level indicates ability to incorporate the new ideas and experiences incoming from those with international experience.

## 4.3 Linking absorptive capacity and innovation

Figure 2 depicts the concept of how absorptive capacity may influence innovation, following the conceptual model of Murovec and Prodan (2009). The left-hand side describes the ordered probit model estimation seen in the previous section. We examine the right-hand side of the conceptual model in this section.

The dependent variable includes a dichotomous variable which takes a value of 1 if a firm reports having performed each of the four types of innovation, including the variable *Any_innovation* which indicates whether a firm reports performing any of the four types of innovation. Assuming the absorptive capacity in period $t$ is predetermined, that is, the level of a firm's absorptive capacity is known at the start of $t$, we first estimate a logit model of the probability of a firm reporting each type of innovation given its demand-pull and science-push absorptive capacity. We then extend the specification to control for employee characteristics using the variables representing international experience and worker skills, firm characteristics and other fixed effects.

The model is specified as follows:

$$Pr(Y_{ijt} = 1) = \Lambda(A_{jt}\beta_1 + E_{jt-2}\beta_2 + F_{jt-2}\beta_3 + X_{jt}\beta_4 + l_r + \zeta_m + \tau_t) \tag{3}$$

where $Y_{ijt}$ represents the binary dependent variable for innovation type $i$ at time $t$. The innovation type refers to the four types defined by BOS or, and a dichotomous variable indicating any of the four types, and $\Lambda$ is the logistic cumulative distribution function. $A_jt$ represents a matrix of predetermined demand-pull and science-push absorptive capacity indices and their quadratic terms for firm $j$ at time $t$. $E_{jt-2}$ represents a matrix of lagged employee characteristics and their interaction term, and $F_{jt-2}$ represents lagged firm characteristics indicating whether the firm engaged in innovative activities, R&D, export, whether the firm operated in skilled area or faced difficulties recruiting workers. $X_{jt}$ is a matrix of other firm level control variables such as firm size, age, outward FDI and foreign ownership. $l_r$, $\zeta_m$ and $\tau_t$ are fixed effects controlling for geographic location, industry and survey year.

The quadratic terms of absorptive capacity reflect the observation that it appears non-innovating firms also have high values of absorptive capacity, that is, the relationship appears non-linear. The implication of this is twofold. First, a firm may continue to develop absorptive capacity in order to be able to respond to or quickly adopt any technological changes that may come about in the industry, or be a fast second mover in a competitive environment as suggested by Cohen and Levinthal (1989, 1990). Second, a firm may reach a point where continuing to innovating becomes difficult in spite of continuous R&D, or development of learning capabilities due to, for example, the advanced technological progress that has already taken place or even the actual difficulty of the domain. The authors classify the fields in which firms operate into more applied versus more pure scientific to make this distinction and confirm this relationship. The non-linear model specification can be used to identify the level from which the probability of firm innovating, despite of absorptive capacity increasing, starts to decline.

# 5 Data

We use microdata about businesses and individuals from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). The LBD contains firm level information from administrative and survey data encompassing a wide range of topics including business practices, financials and employment. The IDI links administrative data from different government agencies and holds detailed individual level information including a person's education, migration and employment information. The IDI and LBD can be linked using the employment information reported through tax data. All data are de-identified, and access to the LBD and IDI are strictly controlled by the government. The significance of the panel data is that it enables use of lagged variables as explanatory variables. The dataset is an unbalanced panel of roughly 44,000 observations, of which around 60% are firms that have responded to the innovation survey in consecutive years.

## 5.1 Sources of information for innovation

Information related to firm innovation and activities used to measure firm absorptive capacity comes from the Business Operations Survey (BOS), carried out annually by Statistics New Zealand since 2005. The population of interest for BOS is all New Zealand firms in the private sector with six or more average number of employees, which are roughly 350,000 firms. The survey is mailed out to a random sample of firms based on a two-way stratification on industry and firm size, and each respondent firm is allocated a final selection weight adjusting for non-response and inactive firms. Response is mandatory under the provisions of the Statistics Act, and the resulting number of usable responses are between 5,000-7,000 per year, eventuating in an average response rate of 80 percent (Fabling & Sanderson, 2016). Our sample is an unbalanced panel data covering 7 surveys from alternating years over the period 2005-17, with a size of roughly 44,000 observations.

The innovation module of BOS follows the OECD guidelines (OECD, 2005), also known as the Oslo manual, on collecting innovation statistics. The survey qualitatively measures the characteristics of firms and their engagement in innovative activities, and the determinants and outcomes of firm innovation. BOS outlines the definition of innovation as:

> The development or introduction of any new or significantly improved activity for this business. This includes products, processes and methods that this business was the first to develop and those that have been adopted from other organisations (Statistics New Zealand, 2017).

BOS classifies four types of innovation, namely new or significantly improved goods or services, new or significantly improved operational processes (methods of producing or distributing goods or services), new or significantly improved organisational or managerial processes (business strategies, structures or routines) and new or significantly improved marketing methods. We construct an indicator variable for each type of innovation in the last two years, and also an indicator whether or not any of the four types of innovation was undertaken in this period.

The survey also asks firms to indicate, regardless of having innovated or not, whether they have undertaken any activities to support innovation such as acquisition of new equipment, other knowledge, implementation of new strategies, market research and employee training. Firms indicating that they have innovated in the four areas or undertaken activities to support innovation are then re-routed to subsequent questions which ask about sources of information and ideas for innovation, and whether the firms have actively participated with other organisations or individuals, at national and international levels, for the purpose of innovation. The responses to these questions reflect a firm's ability to recognise and exploit the value of spillovers and apply it to produce an innovation outcome. Similar to Murovec and Prodan (2009) and Harris and Le (2018), we use the variables indicating firms' use of external information and cooperation with external agents as measurement variables of latent variable absorptive capacity.

## 5.2 Employee characteristics

A novel feature of this study comes from incorporating measures of employee characteristics derived directly from individual level data in Statistics New Zealand's IDI to capture individual level absorptive capacity. The respondent firms of BOS are used to identify individuals in the IDI through employment data, which come from the Employer Monthly Schedule (EMS) in the Inland Revenue dataset. Employers are required to report employment, wage and tax information for all of their employees at the end of each month. There are several levels of firm identification in the LBD, we consider all plants (PBNs) associated with each business unit (ENTs) in the sample, and select the plant with the highest number of full-time employees during the balance year each firm has indicated in their response. When a business unit has several plants with the same number of full-time employees, we select the location based on the previous or the following year for firms participating across multiple years, and apply a random selection for firms participating only in one survey year.

A key variable of interest for this study is employees' *international experience*. This information is obtained from passport-scan border crossing records from the Ministry of Business, Innovation and Employment (MBIE). The information allows distinction of migrants from departing residents through unique exit date values assigned to them in their first record which only has entry information.

Based on this information, we construct a linked employer-employee dataset which contains information on the length of service at a firm measured in counts of EMS reports, international experience and education for each employee for the period. By construction, the dataset captures the movement of employees between firms that have participated in BOS over the period 2005-17.

**Identifying employee experience and skills** We construct four continuous variables to indicate share of workers with international experience. We define individuals with international experience as those having spent time overseas for one or more years within the two year period preceding their employment at a firm in New Zealand. This includes recent migrants who entered New Zealand for the first time within the two-year period prior to employment.

The first variable, *intl_experience*, measures the share of workers who fit in the category, by taking the number of tax reports filed for individuals identified as having international experience, divided by the total number of tax reports for all workers at the firm during that time.

The second variable, *intl_exposure*, measures the share of workers who have previously worked in a firm that had a share of 20% or more of total workers with international experience in the previous time period. This captures the workers at firms that are within the threshold if they are still employed, as well as those workers who previously worked at such firms and are now employed at another firm. This variable tries to capture the "indirect" international experience of a worker through co-workers with actual international experience. Employees with international experience may bring new ideas as well as share their experience in learning which they have accumulated during their time in a new environment.

The third variable, *mgr_intl_experience* is similar to the variable *intl_experience*, but only counts the international experience of employees that are considered to be in management. Firms indicate the percentage share of managers and professionals among staff in the survey data. Based on the assumption that this group of staff are also the highest wage earners in a firm, we rank the average of the monthly gross earnings rate of all individuals employed at a firm by two-year interval from highest to lowest, and select the individuals in the top percentage equivalent to the share obtained from BOS responses. For example, if a firm indicates that 25% of the overall workforce are managers or professionals, we take the top 25% of all employees who were employed at the firm during the two-year period ending at the balance date. We then aggregate the number of managers with international experience and divide by the total number of managers to obtain the share of managers with international experience.

The fourth variable, *mgr_intl_exposure*, applies the logic used for the share of total employees with *intl_exposure* to the share of managers with international experience.

One major difference between the variables that consider all employees and the variables that consider managers and professionals is that the first two do not take into account individual worker skills, while the latter two indicate international experience of high skilled employees. The definition of share of high-skilled migrant/returnee in the study by McLeod et al. (2014) is comparable to *mgr_intl_experience*, and the weaker correlation between the current and lagged variables is also present for *mgr_intl_experience* and *mgr_intl_exposure*. The pairwise correlation calculations for the current and lagged variables of *intl_experience*, *intl_exposure*, *mgr_intl_experience* and *mgr_intl_exposure* are 0.82, 0.78, 0.42 and 0.54 respectively.

The education information from the Ministry of Education and Census datasets in the IDI only covers roughly 60% of the individuals in our linked employer-employee dataset. The missing data are mainly for older workers and migrant workers. Running a logit model on tertiary education completion status controlling for gender, age and industry generated a poor model fit, with the classification statistics indicating a low rate of correctly classified fitted values, and the null hypothesis that the independent variables had no effect on the dependent variable could not be rejected. Education is an important variable to consider in analysing effects of human capital, because it directly impacts individual's skill levels and the diversity of knowledge at firm level. There is also the potential issue of omitted variable bias when using only the international experience as an indicator of individual level absorptive capacity, as it could be the case that more high skilled people choose to go overseas.

In light of lack of usable education completion data that covers all individuals in the dataset, we use the worker fixed effects developed by Fabling and Maré (2015b),[2] to identify a proxy for worker skill. Existing studies also rely on these measures to proxy for individual's skills.[3] We construct a measure, *wfe*, by computing a geometric mean of skill across all workers employed at the firm over the two year period, adjusted by full-time employment.

The firm level variables indicating average worker skills and the share of employees with international experience are continuous variables, therefore, the unit of measurement of these variables is important in order to interpret the coefficients of the model. The share of employees is a straightforward measurement in percentage terms, so a one-unit increase indicates a 1% point increase in the variable. The worker skills proxy is a nominal value obtained from the fixed effects model described earlier, and is therefore difficult to interpret meaningfully. We standardise the worker skills variable to have zero mean and one standard deviation, so a one-unit increase indicates an increase in *wfe* by one standard deviation.

In addition to using information from individual level data aggregated at firm level, we use information collected at firm level from responses to questions in BOS that may affect absorptive capacity and innovation from human capital perspective, such as difficulty experienced in recruiting staff, or whether the firm is operating in a skilled labour area.

## 5.3 Firm dynamics

Appropriability of innovation, or the extent of benefits firms can capture from innovating, affects firms' decision to innovate. This information comes from BOS question which asks firms to indicate the means used to protect intellectual property. We distin-

[2] Fabling and Maré (2015a) have developed a number of derived tables in the IDI and LBD to address limitations of some data. These tables have been made available for all researchers meeting Statistics New Zealand criteria for access to the IDI.

[3] Maré et al. (2015) use this data to measure a skill-adjusted labour input variable to estimate a production function for New Zealand economy and to investigate the effect of worker skill levels on firm productivity and growth. McLeod et al. (2014) adopt this approach in their study on the role of migrants on probability of firm innovation in New Zealand. Sin et al. (2014) also use this measure to investigate the effect of migrants skill levels on firm's international engagement.

guish two types of protection methods, formal and informal, and construct a dummy variable for each type, *appr_formal* and *appr_informal*, to indicate if the firm is using at least one of the two specified types of protection method.

We develop a measure of market power that is similar in essence to the price-cost margin, but as it is not feasible to observe marginal cost or the price per unit of output, we consider the gross output and expenditure to infer market power from the ability of a firm to recover costs. Using the available accounting data from AES and IR10, the profit margin equals:

$$\text{Profit Margin} = \frac{\text{Total Income} - \text{Commonly Measured Expenditure}}{\text{Total Income}} \tag{4}$$

The identification method for both variables follows largely Fabling and Maré (2015b). We construct a measure of capital and output in ways that data from both sources can be used interchangeably. If a value for a component is missing, we do not substitute values from the other data source, implying both income and expenditure variables come from the same source. As a rule, AES is used as the primary source when values from both data sources are available. We also include an indicator variable for values using AES as the data source, *aes_flag*, as values from AES tend to be lower in general. The resulting measure, *prof*, behaves as expected with most values below one. A value closer to one implies that the firm is able to gain larger profits, indicating lower competition.

This measure allows us to investigate the relationship between competition and absorptive capacity or innovation. Schumpeter (1943) described innovation in a competitive environment as a "creative destruction", and suggested the rate of innovation is decreasing in competition in a linear relationship. Aghion et al. (2005) have shown an inverted-U relationship between competition and innovation. In this model, the incumbent firms consider the difference between pre-innovation rents and post-innovation rents. We test the non-linear relationship using the profit margin variable.

As an alternative measure of market structure, we use the questions in BOS which ask firms to indicate the level of competition in the industry to construct indicator variables for market conditions from a competitive standpoint, indicating the level of competition in the market as the firm identifies.

Existing studies on absorptive capacity and innovation in New Zealand firms found export and R&D to be positively correlated to both dependent variables. As mentioned in the related literature section, R&D and its "two faces" is the key idea of the theory of absorptive capacity. Aghion, Bergeaud et al. (2018) suggest that export impacts innovation directly through increasing the market size. A firm which enters an export market has an incentive to innovate in order to capture more demand and therefore higher post innovation rents, particularly for firms close to the technological frontier and higher market share.

New Zealand firms' own foreign direct investment and foreign ownership were also found to have a statistically significant correlation with absorptive capacity and innovation. We construct dummy variables to indicate whether a firm has foreign direct investments and whether a firm is fully, partly or not owned by a foreign parent company to control for the correlation.

We control for firm size using the 12-month moving average number of employees at the end of the balance period indicated in BOS, and also use the balance date to obtain years of operation from the LBF. Geographic location of firm is based on the plant with most active employment history. The industry control variable uses the ANZSIC06 industry classification.

# 6 Results

## 6.1 Absorptive capacity measurement

Table 1 shows the results of the SEM, with standardised coefficients for comparison and grouped by each component of the model. The structural component of the model indicates that the overall absorptive capacity, measured by R&D, export and innovation outcomes, is more highly correlated with demand-pull absorptive capacity, indicated by the higher coefficient value.

The coefficients of the latent variable and constant terms in the measurement components, although not reported here, are all positive implying that the model is capturing the positive relationship between absorptive capacity and the probability of firms using different sources of information and engaging in activities such as cooperative arrangements with other agents, R&D, export and innovation.

Figures B4 and B5 show jitter plots overlaid with boxplots of demand-pull and science-push absorptive capacity estimated using the SEM method. The graphs show the information for innovating and non-innovating firms and by industry. The absorptive capacity values have been standardised to have zero mean and one standard deviation for comparison. The indicator variable *Any_innovation* takes a value of one if a firm has responded as having performed any of the four types of innovation in BOS defined previously. The jitter randomly allocates each data point along the y-axis to avoid overlapping of data points and allows to see the density of data in each industry classification. The largest industries by number of firms in the sample are Manufacturing, Professional, Scientific and Technical Services and Wholesale Trade.

Innovating firms clearly have higher values of demand-pull absorptive capacity. The data appears to be skewed to the right in general, but the range of values for innovating firms seems reasonably spread out. Science-push absorptive capacity appears

Table 1: Structural equation model of absorptive capacity

| Standardised | $\hat{\beta}$ | Z-value |
|---|---|---|
| *Structural* | | |
| Overall absorptive capacity | | |
| Demand-pull | 0.892 | 98.1 |
| Science-push | 0.692 | 45.1 |
| *Measurement* | | |
| Demand-pull absorptive capacity | | |
| Information from customers | 0.685 | 110.5 |
| Information from suppliers | 0.631 | 57.3 |
| Information from other businesses | 0.628 | 76.5 |
| Information from professional advisors, consultants, banks, accountants | 0.573 | 60.1 |
| Information from conferences, trade shows, exhibitions | 0.643 | 96.4 |
| Information from industry or employer organisations | 0.550 | 53.1 |
| Cooperative arrangements with NZ customers | 0.526 | 52.6 |
| Cooperative arrangements with NZ suppliers | 0.525 | 45.5 |
| Cooperative arrangements with other NZ businesses | 0.488 | 43.3 |
| Cooperative arrangements with overseas customers | 0.321 | 18.2 |
| Cooperative arrangements with overseas suppliers | 0.341 | 25.0 |
| Cooperative arrangements with other overseas businesses | 0.322 | 26.1 |
| Science-push absorptive capacity | | |
| Information from books, journals, patent disclosures or Internet | 0.500 | 34.4 |
| Information from universities or polytechnics | 0.608 | 54.5 |
| Information from crown or other research institutes | 0.611 | 36.6 |
| Information from government agencies | 0.524 | 47.0 |
| Cooperative arrangements with NZ universities or polytechnics | 0.566 | 29.2 |
| Cooperative arrangements with NZ crown or other research institutes | 0.578 | 24.2 |
| Cooperative arrangements with overseas universities or polytechnics | 0.273 | 13.9 |
| Cooperative arrangements with overseas crown or other research institutes | 0.218 | 13.4 |
| Overall absorptive capacity | | |
| Product innovation | 0.552 | 52.7 |
| New operational process | 0.562 | 70.7 |
| New organisational or managerial process | 0.569 | 71.3 |
| New marketing methods | 0.552 | 67.5 |
| R&D | 0.404 | 22.9 |
| Export | 0.172 | 9.4 |
| Observations | 40,788 | |
| Log-pseudo-likelihood | -53,000 | |

Observations randomly rounded to base 3.
Robust standard errors adjusted for 167 clusters in ANZSIC06 3-digit industry classification code.
Estimates of the constant for each endogenous relationship not reported.

to be even more skewed to the right. The difference between science-push absorptive capacity for innovating and non-innovating firms is less than it is for demand-pull absorptive capacity. The data suggest that, in general, the science-push absorptive capacity levels of innovating firms are not much higher relative to absorptive capacity levels of non-innovating firms. Both distributions have long tails and outliers.

**Demand-pull or science-push?** The strong non-normality indicated in the jitter plots and kernel density plot in Figure B7 suggests examining the median values in comparing demand-pull and science-push absorptive capacity levels. Figure 3 shows the standardised median values of demand-pull and science-push absorptive capacity by industry, ordered from the highest to the lowest demand-pull absorptive capacity.

The total absorptive capacity across all industries indicates that in general, demand-pull absorptive capacity is higher than science-push absorptive capacity. This is not surprising as more firms are utilising sources of information related to the market conditions (as seen in Figures B1 and B2). As Cohen and Levinthal (1989) pointed out, exploiting knowledge spillovers requires relatively less effort if the knowledge sought after is more targeted, and therefore firms are able to build higher absorptive capacity.

Figure B6 shows the median values for overall absorptive capacity. The order of the industries is largely similar to the demand-pull absorptive capacity, apart from a switch between Wholesale Trade and Information, Media and Telecommunications. The median overall absorptive capacity is higher for Information, Media and Telecommunications industry. Considering the differences in the measurement variables between the demand-pull absorptive capacity and the overall absorptive-capacity, this may mean that while the Wholesale industry is using external knowledge and cooperative measures more than the Information, Media and Telecommunication industry, firms in the latter industry actually report more instances of innovation, R&D and export.

Figure 3: Median demand-pull and science-push absorptive capacity by industry (standardised)

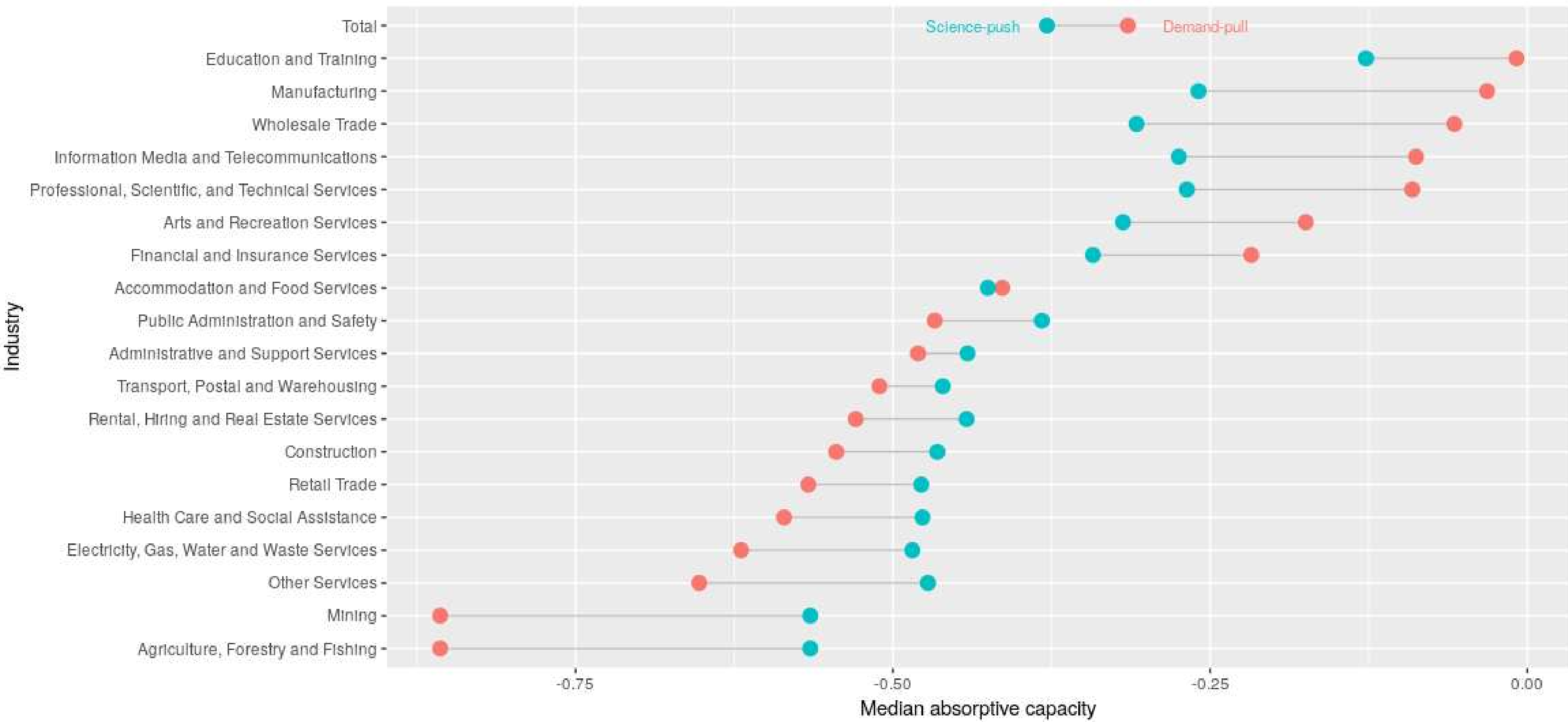


Table 2: Descriptive statistics of absorptive capacity, international experience and worker skills

| *Variables* | p10 | Median | p90 | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|---|---|
| intl_experience$_{t-2}$ | 0% | 5.9% | 19.6% | 8.8% | 10.5 | 0% | 93.5% |
| mgr_intl_experience$_{t-2}$ | 0% | 0% | 20% | 6.1% | 12.3 | 0% | 100% |
| *Standardised* | | | | | | | |
| wfe$_{t-2}$ | -1.300 | 0.164 | 1.032 | 0.288 | 0.994 | -4.168 | 8.356 |
| intl_experience$_{t-2}$ | -0.812 | -0.290 | 0.926 | -0.377 | 0.926 | -0.812 | 7.466 |
| mgr_intl_experience$_{t-2}$ | -0.487 | -0.487 | 1.093 | -0.002 | 0.971 | -0.487 | 7.412 |
| AC_dp | −0.959 | −0.315 | 1.423 | 0 | 1 | −0.959 | 4.453 |
| AC_sp | −0.585 | −0.379 | 1.049 | 0 | 1 | −0.670 | 7.520 |

## 6.2 Determinants of absorptive capacity

Table 3 shows the results of the full model specification for both demand-pull and science-push absorptive capacity quartiles. Columns (1) and (3) were run using the variable *intl_experience* and (2) and (4) were run using the *mgr_intl_experience*. We discuss the results of the ordered probit model in two parts, to illustrate the interaction effect of continuous variables and quantify the effect of discrete variables. We first present the implications of the interaction term between the variables representing international experience and worker skills in a more graphical way using representative values. We then discuss the effects of discrete control variables using average marginal effects.

**Interaction effect of international experience and worker skills** The interpretation of interaction terms of continuous variables is ambiguous, particularly in the context of ordered discrete outcomes. We illustrate the nature of the effect by comparing the predicted probability of being classified to the different quartile groups when the variables of interest are fixed at some representative values, which are the median, 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile values.

Figure 4 shows the effect of the interaction term in model (1), that is, the effect of the interaction term on the predicted probability of a firm's demand-pull absorptive capacity being classified in a quartile group at fixed levels of the lagged values of *intl_experience* and *wfe*. These variables are fixed at the median, 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile values, which are shown in Table 2. *intl_experience* values increase along the horizontal direction and *wfe* increase vertically. The effect from other covariates are average marginal effects using observed values.

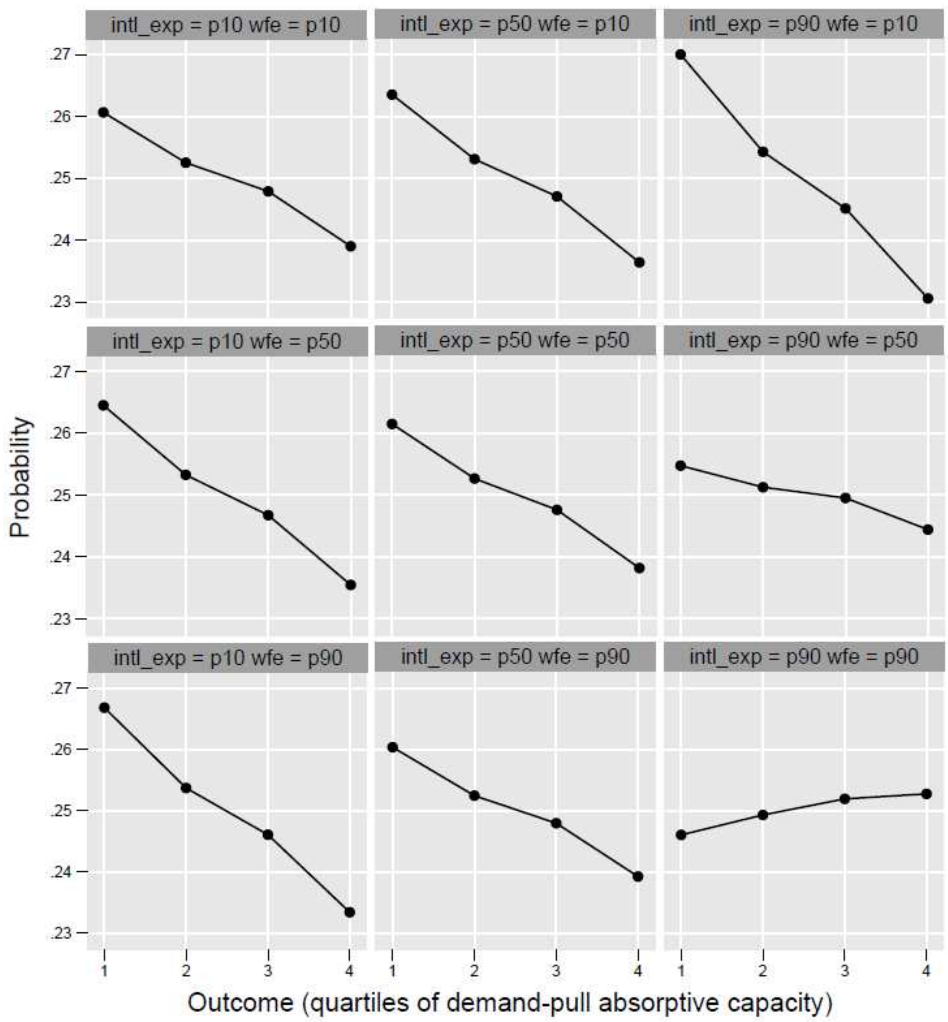
The top left graph shows when both variables are low, at the 10$^{\text{th}}$ percentile. In this case, a firm's absorptive capacity would most likely be classified in the lowest quartile, which is unsurprising. The subsequent graphs indicate that if either of the two variables is disproportionately higher than the other, the probability of a firm's

Table 3: Ordered probit regression of demand-pull and science-push absorptive capacity on employee and firm characteristics (full specification model coefficients)

| | *Demand-pull absorptive capacity* | | *Science-push absorptive capacity* | |
|---|---|---|---|---|
| *Variables* | (1) | (2) | (3) | (4) |
| intl_experience$_{t-2}$ | 0.001*** | | 0.002* | |
| | (0.001) | | (0.001) | |
| wfe$_{t-2}$ | -0.009 | 0.003 | -0.009 | 0.000 |
| | (0.011) | (0.010) | (0.011) | (0.010) |
| (intl_experience × wfe)$_{t-2}$ | 0.002*** | | 0.002*** | |
| | (0.001) | | (0.001) | |
| mgr_intl_experience$_{t-2}$ | | 0.002*** | | 0.003*** |
| | | (0.001) | | (0.001) |
| (mgr_intl_experience × wfe)$_{t-2}$ | | 0.001* | | 0.001* |
| | | (0.001) | | (0.001) |
| prod_innovation$_{t-2}$ = 1 | 0.237*** | 0.237*** | 0.235*** | 0.235*** |
| | (0.019) | (0.019) | (0.020) | (0.020) |
| new_op_process$_{t-2}$ = 1 | 0.201*** | 0.202*** | 0.204*** | 0.206*** |
| | (0.020) | (0.020) | (0.020) | (0.020) |
| new_org_mgmt_process$_{t-2}$ = 1 | 0.269*** | 0.268*** | 0.278*** | 0.277*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| new_mktng_methods$_{t-2}$ = 1 | 0.245*** | 0.245*** | 0.228*** | 0.229*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| R&D$_{t-2}$ = 1 | 0.365*** | 0.363*** | 0.426*** | 0.425*** |
| | (0.024) | (0.024) | (0.025) | (0.025) |
| export$_{t-2}$ = 1 | 0.252*** | 0.251*** | 0.277*** | 0.276*** |
| | (0.017) | (0.017) | (0.017) | (0.017) |
| appr_formal$_{t-2}$ = 1 | 0.132*** | 0.132*** | 0.134*** | 0.133*** |
| | (0.017) | (0.017) | (0.017) | (0.017) |
| appr_informal$_{t-2}$ = 1 | 0.197*** | 0.197*** | 0.201*** | 0.201*** |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| prof$_{t-2}$ | -0.019 | -0.019 | -0.001 | -0.002 |
| | (0.026) | (0.026) | (0.027) | (0.027) |
| prof$^2_{t-2}$ | -0.001 | -0.001 | 0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| NZ_fdi_out= 1 | 0.176*** | 0.176*** | 0.207*** | 0.208*** |
| | (0.030) | (0.030) | (0.030) | (0.030) |
| full_foreign_owned= 1 | -0.058** | -0.062** | -0.057** | -0.063** |
| | (0.025) | (0.025) | (0.025) | (0.025) |
| Observations | 22365 | 22362 | 22365 | 22362 |
| Pseudo $R^2$ | 0.082 | 0.082 | 0.087 | 0.087 |
| Likelihood ratio test | 5089.4 | 5095.8 | 5386.2 | 5401.0 |

Observations randomly rounded to base 3.
Standard errors in parentheses.
Firm size, age, industry and location fixed effects included but not reported.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Predicted probability for each quartile of demand-pull absorptive capacity at 10$^{th}$, 50$^{th}$ and 90$^{th}$ percentiles of lagged international experience and worker skills variables



absorptive capacity being classified into the lowest quartile increases, and at the same time the probability of being in the higher quartile group decreases. This relationship is most striking when the share of international experience is high but the average worker skills is relatively low. Firms having median values for these variables are still more likely to be classified into the lowest quartile group.

As expected, the effect changes only when both variables are high in the $90^{\text{th}}$ percentile, in which case a firm's demand-pull absorptive capacity level is most likely to be classified in the top quartile range. It appears however, that the probability of getting classified in lower quartile groups does not decrease by much, as the slope of the curve becomes flatter at the $90^{\text{th}}$ percentile. The small p-values associated with the coefficients of variables related to international experience and average worker effects suggest that including the employee characteristics variables in the model improves the model fit, *but the effect on the probability is quite small*, within a range of plus or minus 0.5% points.

The weak magnitude of economic significance of the effect of employees is also observed in the results of the full model specification in McLeod et al. (2014). The authors find that in their full model specification, the share of high-skilled recent migrants is statistically significant, and quantify that the effect of a 1% point increase in the share of high-skilled recent migrants a firm's workforce increases the probability of firms innovating by 0.66% points.

**Average marginal effect of past innovative activities** The lagged variables indicating whether the firm performed four types of innovation are all statistically significant. Table 4 shows the average marginal effects of the lagged variables. As these variables are binary indicators, the interpretation is more straightforward than the nonlinear term of continuous variables. A unit change for in the case of binary variables represents the change from the base level of zero.

The results indicate that new organisational or management process had the largest average marginal effect on the probability of demand-pull absorptive capacity out of the four types of innovation. As seen before in figure B3, more firms indicate as having performed new organisational or management process out of the four innovation types. This implies that firms who implement a new organisational or management process are also more likely to use external sources of information and cooperative measures. An organisational or managerial process is defined in the BOS questionnaire as the business' strategies, structures or routines. The result reflects the importance of the organisational structure in managing tacit knowledge and communicating new incoming information within and across units. Having implemented a new organisational or management process increases the probability of a firm's demand-pull or science-push absorptive capacity being classified in first two quartile ranges by 7%

Table 4: Average marginal effect of past innovation, R&D and export

| | Model (1): *Demand-pull absorptive capacity* | | | | Model (3): *Science-push absorptive capacity* | | | |
|---|---|---|---|---|---|---|---|---|
| *Variables* | $\frac{\partial Pr(q=1)}{\partial F}$ | $\frac{\partial Pr(q=2)}{\partial F}$ | $\frac{\partial Pr(q=3)}{\partial F}$ | $\frac{\partial Pr(q=4)}{\partial F}$ | $\frac{\partial Pr(q=1)}{\partial F}$ | $\frac{\partial Pr(q=2)}{\partial F}$ | $\frac{\partial Pr(q=3)}{\partial F}$ | $\frac{\partial Pr(q=4)}{\partial F}$ |
| prod_innovation$_{t-2}$ = 1 | -0.067*** | -0.018*** | 0.018*** | 0.066*** | -0.066*** | -0.017*** | 0.018*** | 0.065*** |
| | (0.005) | (0.002) | (0.001) | (0.006) | (0.005) | (0.002) | (0.001) | (0.006) |
| new_op_process$_{t-2}$ = 1 | -0.057*** | -0.014*** | 0.016*** | 0.056*** | -0.057*** | -0.014*** | 0.016*** | 0.056*** |
| | (0.005) | (0.002) | (0.001) | (0.006) | (0.005) | (0.002) | (0.001) | (0.005) |
| new_org_mgmt_process$_{t-2}$ = 1 | -0.076*** | -0.020*** | 0.021*** | 0.075*** | -0.078*** | -0.020*** | 0.022*** | 0.077*** |
| | (0.005) | (0.002) | (0.001) | (0.005) | (0.005) | (0.002) | (0.001) | (0.005) |
| new_mktng_methods$_{t-2}$ = 1 | -0.069*** | -0.018*** | 0.019*** | 0.068*** | -0.064*** | -0.016*** | 0.018*** | 0.063*** |
| | (0.005) | (0.002) | (0.001) | (0.006) | (0.005) | (0.002) | (0.001) | (0.006) |
| R&D$_{t-2}$ = 1 | -0.097*** | -0.032*** | 0.022*** | 0.107*** | -0.111*** | -0.039*** | 0.025*** | 0.126*** |
| | (0.006) | (0.003) | (0.001) | (0.008) | (0.006) | (0.003) | (0.001) | (0.008) |
| export$_{t-2}$ = 1 | -0.072*** | -0.017*** | 0.020*** | 0.069*** | -0.079*** | -0.019*** | 0.022*** | 0.075*** |
| | (0.005) | (0.001) | (0.001) | (0.005) | (0.005) | (0.001) | (0.001) | (0.005) |
| appr_formal$_{t-2}$ = 1 | -0.038*** | -0.008*** | 0.011*** | 0.036*** | -0.038*** | -0.008*** | 0.011*** | 0.036*** |
| | (0.005) | (0.001) | (0.001) | (0.005) | (0.005) | (0.001) | (0.001) | (0.005) |
| appr_informal$_{t-2}$ = 1 | -0.057*** | -0.012*** | 0.017*** | 0.053*** | -0.059*** | -0.012*** | 0.017*** | 0.054*** |
| | (0.005) | (0.001) | (0.001) | (0.004) | (0.005) | (0.001) | (0.001) | (0.004) |
| Observations | 22365 | | | | 22365 | | | |
| Pseudo $R^2$ | 0.082 | | | | 0.087 | | | |
| Likelihood ratio test | 5089.4 | | | | 5386.2 | | | |

Observations randomly rounded to base 3.
Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

points and 2% points respectively.

Engaging in R&D in the previous period has the largest average marginal effect on the probability of a firm having higher values of absorptive capacity. Recall that the absorptive capacity indices have been measured using variables indicating whether firms take advantage of using external sources of information and sharing knowledge through cooperative arrangements. The results of the model suggests that R&D in the previous period increases the probability of demand-pull absorptive capacity being in the top quartile by 11% points. For science-push absorptive capacity, R&D in the previous period increased the probability of a firm having science-push absorptive capacity in the top quartile range by 13% points. These results are in line with existing studies, and suggest that R&D indeed has a dual role of enabling firms to benefit from exploiting external information, or spillovers. Furthermore, the bigger average marginal effect of R&D on science-push absorptive capacity supports the argument in Cohen and Levinthal (1989) that R&D matters more for firms seeking to learn less targeted, broader and technological knowledge, and therefore are required to invest more effort into it.

Firms that exported in the previous period are approximately 7 to 8% points more likely to have an absorptive capacity level classified in the top quartile group. The positive relationship between export and absorptive capacity potentially translates into firms having access to a larger pool of external knowledge or spillovers and therefore seeing more opportunities to benefit from them.

Firms that used appropriability measures in the previous period, either formal or informal measures, are more likely to have absorptive capacity levels classified in the higher quartile ranges by around 5% points. This may be interpreted as firms that are aware of and actively using appropriability measures are more likely to engage in activities that increase their absorptive capacity.

The lagged profit margin variable is not significant, nor is the squared term. The insignificance may be due to the quality of the profit data.

In a previous study of absorptive capacity in New Zealand firms by Harris and Le (2018), absorptive capacity was significantly correlated with whether firms had foreign ties. It appears that while both variables indicating outward foreign direct investment (FDI) from New Zealand firms and firms fully owned by foreign entities are statistically significant, only the outward FDI variable is positively correlated with the probability of a firm having higher levels of absorptive capacity. This may indicate that the variable might be explaining another effect. The negative correlation between foreign ownership may potentially be explained by firms considering their parent entities located overseas as the primary source of information, and taking a more passive approach to seeking external information or cooperation within New Zealand.

The results of the full model indicate that R&D contributes mostly to the likelihood of a firm having high absorptive capacity. Past innovative activities all have statistically significant effect on the probability of having higher values of absorptive capacity, with experience of having implemented a new organisational and managerial process contributing the largest amount. Export and use of appropriability mechanisms also increase the probability of a firm having a higher absorptive capacity relative to other firms that do not engage in these activities. There is no evidence that a firm's profit margins affect the probability of its absorptive capacity being at different levels.

As for the effect of employee characteristics represented by international experience and worker skills proxy, there is strong evidence that the effect of employees with international experience on the probability of a firm's absorptive capacity being classified into each quartile group depends on the average skill level of workers, and vice versa. The interaction effect suggests that the probability of the firm's absorptive capacity being in the highest quartile is the greatest when both the share of employees with international experience and average worker skills are high.

## 6.3 Absorptive capacity and innovation

Table 5 shows the results of fitting full specifications of the model on the dependent variable *Any_innovation*, which include employee and firm characteristics and fixed effects for firm location, size, age and industry. We choose to include the *mgr_intl_experience* variable, as this variable effectively explains the same variation in the data as the other *intl_experience* variable, as seen in the results of the ordered probit model in the previous section.

The size of the coefficients for demand-pull absorptive capacity is larger than science-push absorptive capacity. As the variables are now on a common scale, this implies that a unit-increase in demand-pull absorptive capacity increases the probability of a firm innovating more than a unit-increase in science-push absorptive capacity. This result is also comparable to the results in Murovec and Prodan (2009) examining the influence of demand-pull and science-push absorptive capacity of firms in Spain and the Czech Republic, in which demand-pull absorptive capacity also had a larger impact on measures of innovation output than science-push absorptive capacity.

Column (1) shows a model specification without the quadratic terms. This does not have any noticeable effect on demand-pull absorptive capacity, but science-push absorptive capacity is statistically significant at 1% level and negatively influences the probability of a firm reporting any of the four types of innovation. This reflects the results in Harris and Le (2018), who find that cooperation with higher education institutions has a negative correlation with probability of firms innovating. The authors suggest that the negative relationship might indicate the difficulty of adopting scientific research into innovative outcome. We suggest the negative sign could be the result of a mis-specification of the model.

Column (2) has the same model specification as column (1), apart from the quadratic terms that are now included. The quadratic terms are still all significant, even in the extended specification. The full model predicts that the probability of a firm innovating starts to decrease at demand-pull absorptive capacity values of 3.45 ($\frac{2.633}{-0.763}$) or above, and science-push absorptive capacity values of 5.39 ($\frac{0.165}{-0.031}$). Comparing the values to the descriptive statistics in Table 2, these are well above the 90$^{\text{th}}$ percentile for both types of absorptive capacity. Therefore, for less than 10% of firms in the sample, the model predicts that the probability of innovating decreases even though they might have high levels of absorptive capacity.

The lagged variables indicating employee characteristics are not statistically significant. The signs of the linear terms are also negative, while the interaction term of the two variables still have a positive sign. The lagged variables of innovation are all significant and positively influence the probability of a firm reporting in the subsequent period. R&D, export and use of appropriability measures are not significant. The insignificance of R&D is quite surprising, but this potentially reflects correlation between R&D and absorptive capacity.

Neither linear nor quadratic term of the profit margin variables is significant in this specification. The positive signs for both terms in the linear specification of column (1) suggest an increasing trend as the profit margin increases. The outward FDI and

Table 5: Logit model of probability of firms innovating conditional on absorptive capacity, employee and firm characteristics

| | Dependent variable: *Any innovation* | | |
|---|---|---|---|
| *Variables* | (1) | (2) | (3) |
| $AC\_dp_t$ | 2.642*** | 2.633*** | 2.622*** |
| | (0.060) | (0.058) | (0.053) |
| $AC\_dp_t^2$ | | -0.763*** | -0.779*** |
| | | (0.023) | (0.021) |
| $AC\_sp_t$ | -0.342*** | 0.165** | 0.226*** |
| | (0.070) | (0.093) | (0.085) |
| $AC\_sp_t^2$ | | -0.031** | -0.032* |
| | | (0.018) | (0.016) |
| $mgr\_intl\_experience_{t-2}$ | -0.023 | -0.032 | -0.017 |
| | (0.023) | (0.024) | (0.021) |
| $wfe_{t-2}$ | -0.010 | -0.003 | -0.003 |
| | (0.023) | (0.025) | (0.022) |
| $(mgr\_intl\_experience \times wfe)_{t-2}$ | 0.017 | 0.022 | 0.014 |
| | (0.020) | (0.022) | (0.019) |
| $prod\_innovation_{t-2} = 1$ | 0.437*** | 0.449*** | 0.441*** |
| | (0.051) | (0.055) | (0.050) |
| $new\_op\_process_{t-2} = 1$ | 0.260*** | 0.266*** | 0.243*** |
| | (0.053) | (0.056) | (0.051) |
| $new\_org\_mgmt\_process_{t-2} = 1$ | 0.214*** | 0.208*** | 0.204*** |
| | (0.051) | (0.054) | (0.049) |
| $new\_marketing\_method_{t-2} = 1$ | 0.181*** | 0.184*** | 0.186*** |
| | (0.052) | (0.056) | (0.050) |
| $R\_D_{t-2} = 1$ | 0.053 | -0.020 | 0.001 |
| | (0.070) | (0.073) | (0.067) |
| $export_{t-2} = 1$ | 0.029 | 0.001 | -0.001 |
| | (0.046) | (0.050) | (0.045) |
| $appr\_formal_{t-2} = 1$ | 0.052 | 0.040 | 0.064 |
| | (0.046) | (0.050) | (0.045) |
| $appr\_informal_{t-2} = 1$ | 0.043 | 0.020 | 0.038 |
| | (0.044) | (0.047) | (0.042) |
| $diffc\_rcrt\_mgr\_prof_{t-2} = 1{=}1$ | 0.089* | 0.100* | 0.065 |
| | (0.049) | (0.053) | (0.048) |
| $diffc\_rcrt\_oth\_staff_{t-2} = 1$ | -0.068 | -0.070 | -0.028 |
| | (0.048) | (0.048) | (0.044) |
| $lack\_personnel_{t-2} = 1$ | 0.074* | 0.031 | 0.022 |
| | (0.043) | (0.046) | (0.042) |
| $skilled\_labour\_mkt_{t-2} = 1$ | -0.095* | -0.085* | -0.009 |
| | (0.047) | (0.051) | (0.045) |
| $prof_{t-2}$ | 0.007 | -0.043 | |
| | (0.085) | (0.091) | |
| $prof^2_{t-2}$ | 0.002 | 0.002 | |

*Continued on next page*

Table 5: *continued from previous page*

| *Variables* | Dependent variable: *Any innovation* (1) | (2) | (3) |
|---|---|---|---|
| | (0.003) | (0.003) | |
| bet_0_2_comp$_t$ = 1 | | | 0.337** |
| | | | (0.112) |
| many_comp_sev_dom$_t$ = 1 | | | 0.426*** |
| | | | (0.107) |
| many_comp_non_dom$_t$ = 1 | | | 0.349*** |
| | | | (0.114) |
| nz_own_out_fdi$_t$ = 1 | 0.208** | 0.268*** | 0.284*** |
| | (0.080) | (0.084) | (0.079) |
| full_foreign_owned$_t$ = 1 | 0.123* | 0.153** | 0.126* |
| | (0.066) | (0.072) | (0.064) |
| constant | -0.522* | 0.073** | -0.228 |
| | (0.316) | (0.345) | (0.333) |
| Observations | 20265 | 20265 | 25170 |
| Pseudo $R^2$ | 0.437 | 0.478 | 0.484 |
| Wald test $\chi^2$ | 3908.3 | 6770.8 | 8325.4 |

Standard errors in parentheses
Firm size, age, location, industry and survey year fixed effects included but not reported.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

foreign ownership are both statistically significant, as was the case in the earlier study by Harris and Le (2018). In the quadratic specification of columns (2) and (3), the coefficient for the profit margin remains statistically insignificant, but the sign for the linear term now has a negative coefficient. This would imply a U-shaped curve with the positive quadratic term, in line with the theory.

The model in column (3) excludes the profit margin variable and instead includes dummy variables to indicate the level of competition in the market as identified by the firm. The variables indicate whether a firm reports as operating in a market with between zero to two competitors, or with many competitors and several dominant players, or with many competitors and no dominant players. The three variables, *bet_0_2_comp*, *many_comp_sev_dom* and *many_comp_non_dom* are all statistically significant and positively correlated. The biggest effect is when firms have identified as having many competitors and several dominant players. As the measure does not indicate the firm's market power, it is difficult to deduce incentives. The positive correlation between the presence of competitors and the probability of firms innovating might indicate that they are innovating to *escape competition*.

Adding quadratic terms of absorptive capacity does not seem to affect the magnitude of the coefficients associated with other variables by much, apart from the lagged R&D variable now changing to a negative sign. This further confirms the correlation between R&D and absorptive capacity and raises the question of which variable should be used. It can be argued that, to measure the total effect of R&D, one should take into account absorptive capacity, as it captures the firm's increased ability to learn, generated as a byproduct of R&D, and also contributes to the likelihood of firms innovation.

We include the variables $diffc\_rcrt\_mgr\_prof_{t-2}$, $diffc\_rcrt\_oth\_staff_{t-2}$, $lack\_personnel_{t-2}$ and $skilled\_labour\_mkt_{t-2}$ to control for hindrances to innovation. The sign is negative for $diffc\_rcrt\_oth\_staff_{t-2}$, but there is no statistical evidence that this variable influences the probability of a firm innovating. Other variables have the opposite sign, but the statistical significance is at best marginal at the 10% level. Mairesse and Mohnen (2010) observe that it is common to see obstacles to innovation having a positive marginal effect on innovation in economic literature using innovation surveys that follow the guidelines in the Oslo manual. They note also that treating for endogeneity may correct the relationship. We use the lagged variables to reflect this, however the signs do not indicate the expected relationship.

Overall, the results of the logit model reveal that both types of absorptive capacity are strongly related to the probability of a firm innovating. Conversely, some of the variables that were identified in earlier studies as having significant effect on the likelihood of firms innovating, such as employee skills, R&D, export and appropriability measures are no longer significant when including absorptive capacity in the specification.

# 7 Conclusions

We measure absorptive capacity in New Zealand firms, investigate factors that influence firm level absorptive capacity, with a focus on capturing the role of employees, and finally examine the influence of absorptive capacity on the likelihood of a firm innovating. The results indicate that New Zealand firms have higher demand-pull absorptive capacity than science-push absorptive capacity, and that R&D has the biggest influence on the probability that a firm's absorptive capacity is high for both demand-pull and science-push absorptive capacity. Absorptive capacity influences the probability of a firm innovating positively.

The results also indicate that the relationship between absorptive capacity and the probability of a firm innovating is non-linear. Some firms do not innovate even though they have high level of absorptive capacity. This may reflect the fact that firms continue to exploit knowledge spillovers in one period not because they are expecting specific innovative results driven on their part, but to enable themselves to recognise valuable new information or respond quickly to competitors' innovation. It may also reflect the difficulty of innovating in a domain.

Between demand-pull and science-push absorptive capacity, demand-pull absorptive capacity has greater effect on the probability of a firm innovating. Based on these results and the cumulative nature of absorptive capacity, continuous R&D efforts that focus on enabling firms to recognise and utilise valuable knowledge relevant to market conditions appear fundamental for innovation in New Zealand firms.

Of particular interest in this study was to investigate the role of employees on firm level absorptive capacity. The results indicate that the economic significance of employee characteristics, while statistically significant, is small in magnitude. The measurement variables used are indicators of activities that directly reflect whether a firm has built some level of absorptive capacity, but not all of the firm's employees engage in those activities. Consequently, it would be of interest to compare the role of individual absorptive capacity of employees involved in units responsible for R&D or specific tasks that reflect efforts to increase the firm's knowledge stock using outside sources of information, as they may have more significant influence on firm absorptive capacity than the relatively weak economic significance observed when considering the characteristics of the overall workforce.

Firm heterogeneity in management of knowledge flows and innovation processes, however, poses difficulty in identifying the role of employees on firm level absorptive capacity. For example, a firm may have many cross-functional units that engage in learning information from outside sources and using this to innovate. In this case, the individual absorptive capacity of employees across the firm matters greatly, and the firm requires a high-skilled workforce overall. On the other hand, a firm may have a specific unit that is solely responsible for R&D. In this case, the organisational structure that influences communication within the firm might matter more than the individual absorptive capacity of all employees, but individual absorptive capacity would still be of great importance for the employees in the unit responsible for R&D. Identifying the channels of knowledge flow in a firm and employees that may exert influence on the nature of incoming knowledge and new knowledge generated is challenging and limited by availability of data.

Alternatively, further research using the IDI may look at individual absorptive capacity as the unit of measurement instead to investigate how spillovers among individuals affect firm level absorptive capacity and innovation. For example, Aghion, Akcigit et al. (2018) use individual patent data merged with firm level data and examine pre and post-invention income benefits generated across all employee groups within the firm inventors are employed at. Aghion and Jaravel (2015) point out that identifying individual's absorptive capacity is important because the existence of spillovers among individuals can induce complementarity effects on the innovation process which may be greater than the effect of individual behaviour.

Lastly, the concept of absorptive capacity is a relevant topic for future research reflecting the new R&D tax credit policy (Taxation (Research and Development Tax

Credits) Act 2019) in New Zealand. The new policy defines R&D more broadly than previously as the government support for R&D through the Callaghan programme was seen as somewhat restrictive to scientific fields and difficult for smaller firms to access. The broader definition of the new policy aims to support a wider range of activities to create new knowledge that generate adequate spillover benefits, and to compensate for the negative incentives from the spillovers. Seeing that demand-pull absorptive capacity has a larger impact on the probability of a firm innovating, the new policy appears to be a step in the right direction. The concept of absorptive capacity will enable measuring not only the returns to R&D on the innovating firm but also its externalities on firms exploiting knowledge spillovers, and therefore, overall social returns.

## References


Aghion, P., Akcigit, U., Hyytinen, A. & Toivanen, O. (2018). On the Returns to Invention within Firms: Evidence from Finland. *AEA Papers and Proceedings*, *108*, 208–12. https://doi.org/10.1257/pandp.20181108

Aghion, P., Bergeaud, A., Lequien, M. & Melitz, M. J. (2018). *The Impact of Exports on Innovation: Theory and Evidence* (No. 24600). NBER Working Paper. https://ideas.repec.org/p/nbr/nberwo/24600.html

Aghion, P., Bloom, N., Blundell, R., Griffith, R. & Howitt, P. (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics*, *120*(2), 701–728. http://www.jstor.org/stable/25098750

Aghion, P. & Jaravel, X. (2015). Knowledge Spillovers, Innovation and Growth. *Economic Journal*, *125*(583), 533–573. https://doi.org/10.1111/ecoj.12199

Cohen, W. M. & Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R&D. *The Economic Journal*, *99*(397), 569–596. http://www.jstor.org/stable/2233763

Cohen, W. M. & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128–152. http://www.jstor.org/stable/2393553

Crescenzi, R. & Gagliardi, L. (2018). The Innovative Performance of Firms in Heterogeneous Environments: The Interplay Between External Knowledge and Internal Absorptive Capacities. *Research Policy*, *47*(4), 782–795. https://doi.org/https://doi.org/10.1016/j.respol.2018.02.006

Ebers, M. & Maurer, I. (2014). Connections Count: How Relational Embeddedness and Relational Empowerment Foster Absorptive Capacity. *Research Policy*, *43*(2), 318–332. https://doi.org/https://doi.org/10.1016/j.respol.2013.10.017

Fabling, R. & Maré, D. C. (2015a). *Addressing the Absence of Hours Information in Linked Employer-Employee Data* (No. 15-17). Motu Working Paper. http://motu-www.motu.org.nz/wpapers/15_17.pdf

Fabling, R. & Maré, D. C. (2015b). *Production Function Estimation Using New Zealand's Longitudinal Business Database* (No. 15-15). Motu Working Paper. http://motu-www.motu.org.nz/wpapers/15_15.pdf

Fabling, R. & Sanderson, L. (2016). *A Rough Guide to New Zealand's Longitudinal Business Database (2nd Edition)* (2nd edition., No. 16-03). Motu Working Paper. http://motu-www.motu.org.nz/wpapers/16_03.pdf

Harris, R. & Le, T. (2018). Absorptive Capacity in New Zealand Firms: Measurement and Importance. *Science and Public Policy*, *46*(2), 290–309. https://doi.org/10.1093/scipol/scy058

Kamien, M. I. & Zang, I. (2000). Meet Me Halfway: Research Joint Ventures and Absorptive Capacity. *International Journal of Industrial Organization*, *18*(7), 995–1012. https://doi.org/https://doi.org/10.1016/S0167-7187(00)00054-0

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (3rd ed.). Guilford Press.

Leahy, D. & Neary, J. (2007). Absorptive Capacity, R&D Spillovers, and Public Policy. *International Journal of Industrial Organization*, *25*, 1089–1108. https://doi.org/10.1016/j.ijindorg.2007.04.002

Li, H. (2016). Developing Shared Knowledge in Growing Firms. *The Journal of Law, Economics, and Organization*, *33*(2), 332–376. https://doi.org/10.1093/jleo/eww016

Lopez-Garcia, P. & Montero, J. M. (2012). Spillovers and Absorptive Capacity in the Decision to Innovate of Spanish Firms: the Role of Human Capital. *Economics of Innovation and New Technology*, *21*(7), 589–612. https://doi.org/10.1080/10438599.2011.606170

Mairesse, J. & Mohnen, P. (2010). Using Innovation Surveys for Econometric Analysis. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation* (pp. 1129–1155). https://doi.org/10.1016/S0169-7218(10)02010-1

Mancusi, M. L. (2008). International Spillovers and Absorptive Capacity: A Cross-Country Cross-Sector Analysis Based on Patents and Citations. *Journal of International Economics*, *76*(2), 155–165. https://doi.org/https://doi.org/10.1016/j.jinteco.2008.06.007

Maré, D. C., Fabling, R. & Stillman, S. (2014). Innovation and the Local Workforce. *Papers in Regional Science*, *93*(1), 183–201. https://doi.org/10.1111/j.1435-5957.2012.00479.x

Maré, D. C., Hyslop, D. R. & Fabling, R. (2015). *Firm Productivity Growth and Skill* (No. 15-18). Motu Working Paper. http://motu-www.motu.org.nz/wpapers/15_18.pdf

McLeod, K., Fabling, R. & Maré, D. C. (2014). *Hiring New Ideas: International Migration and Firm Innovation in New Zealand* (No. 14-14). Motu Working Paper. http://motu-www.motu.org.nz/wpapers/14_14.pdf

Miguélez, E. & Moreno, R. (2015). Knowledge Flows and the Absorptive Capacity of Regions. *Research Policy*, *44*(4), 833–848. https://doi.org/https://doi.org/10.1016/j.respol.2015.01.016

Murovec, N. & Prodan, I. (2009). Absorptive Capacity, its Determinants, and Influence on Innovation Output: Cross-Cultural Validation of the Structural Model. *Technovation*, *29*(12), 859–872. https://doi.org/https://doi.org/10.1016/j.technovation.2009.05.010

Nemet, G. F. (2009). Demand-Pull, Technology-Push, and Government-Led Incentives for Non-Incremental Technical Change. *Research Policy*, *38*(5), 700–709. https://doi.org/https://doi.org/10.1016/j.respol.2009.01.004

OECD. (2005). *Oslo Manual Guidelines for Collecting and Interpreting Innovation Data.* (3rd ed..). Organisation for Economic Co-operation; Development : Statistical Office of the European Communities. https://doi.org/https://doi.org/10.1787/9789264013100-en

Schumpeter, J. A. (1934). *The Theory of Economic Development : an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*. Harvard University Press.

Schumpeter, J. A. (1943). *Capitalism, Socialism and Democracy*. Routledge. CRCnetBASEe-Books

Schweisfurth, T. G. & Raasch, C. (2018). Absorptive Capacity for Need Knowledge: Antecedents and Effects for Employee Innovativeness. *Research Policy*, *47*(4), 687–699. https://doi.org/https://doi.org/10.1016/j.respol.2018.01.017

Sin, I., Jaffe, A. B., Maré, D. C. & Sanderson, L. (2014). *Exporting, Innovation and the Role of Immigrants* (No. 14-15). Motu Working Paper. https://doi.org/http://dx.doi.org/10.2139/ssrn.2537149

Statistics New Zealand. (2017). *Business Operations Survey 2017*. http://cdm20045.contentdm.oclc.org/digital/collection/p20045coll2/id/709/rec/12

Taxation (Research and Development Tax Credits) Act 2019. (2019). http://legislation.govt.nz/act/public/2019/0015/latest/LMS110236.html

Vinding, A. L. (2006). Absorptive Capacity and Innovative Performance: A Human Capital Approach. *Economics of Innovation and New Technology*, *15*(4-5), 507–517. https://doi.org/10.1080/10438590500513057

# A Theoretical Background

We present a general theoretical model specified by Leahy and Neary (2007) to associate the role of employees to firm absorptive capacity. The model assumes that firms are symmetric, and a firm's marginal cost is decreasing in own R&D and spillovers generated by rival R&D. Define $c$, $x$, $y$, $X$ and $\delta$ as follows:

$$\begin{aligned} c &= \text{firm's marginal cost function} \\ x &= \text{firm's own R\&D} \\ y &= \text{usable rival R\&D} \\ X &= \text{actual rival R\&D} \\ \delta &= \text{difficulty of absorbing usable rival R\&D, } 0 \leq \delta \leq 1 \end{aligned}$$

The firm's marginal cost function is a function of its own R&D and the usable rival's R&D.

$$c = c(x, y). \tag{5}$$

The effectiveness of the firm's own R&D is defined as $\theta$, and is the first derivative of the cost function with respect to its own R&D.

$$\theta \equiv -\frac{\partial c}{\partial x} > 0. \tag{6}$$

The extent of spillovers is defined as the ratio of the partial derivatives of the cost function with respect to usable rival R&D, $y$, and its own R&D, $x$.

$$\beta \equiv \frac{\partial c}{\partial y} / \frac{\partial c}{\partial x} \geq 0, \text{ where } 0 \leq \beta \leq 1. \tag{7}$$

The firm's absorptive capacity is the ratio of usable rival R&D to actual rival R&D, $\frac{y}{X}$, with the ratio increasing in its own R&D, $x$. Usable rival R&D is dependent on the knowledge generated by the firm's own R&D, actual rival R&D, and the exogenous parameter $\delta$.

$$y = y(x, X, \delta). \tag{8}$$

The two extreme cases are when $\delta$ is zero, usable rival R&D is equal to actual rival R&D, and when $\delta$ is one, absorptive capacity is zero. Assume, trivially, that usable rival R&D cannot exceed actual rival R&D and usable rival R&D is strictly less than actual rival R&D when the exogenous parameter $\delta$ is positive. This ensures absorptive capacity takes a value between zero and one, that is, $y \leq X$. Assume further that both own R&D and actual rival R&D increase usable R&D at margin except in the extreme cases. Combining equations 5 and 8, the firm's marginal cost function can be re-written as follows.

$$\tilde{c}(x, X, \delta) \equiv c[x, y(x, X, \delta)]. \tag{9}$$

Given $\tilde{c}$, define $\tilde{\theta}$ such that the full effectiveness of own R&D on marginal cost taking into account the impact of own R&D on usable rival R&D, is greater than or no less than the effectiveness of own R&D measured directly. Define also, the extent of *effective* spillover, that is, the ratio of marginal returns to actual rival R&D and own R&D is no more than or equal to the ratio of marginal returns realised from the overall effect of own R&D on spillovers.

$$\tilde{\theta} \equiv -\frac{\partial \tilde{c}}{\partial x} \geq \theta \text{ and } \tilde{\beta} \equiv \frac{\partial \tilde{c}}{\partial X} / \frac{\partial \tilde{c}}{\partial x} \leq \beta. \tag{10}$$

Equation 10 shows that modelling usable rival R&D as a function of own R&D implies that the effectiveness of firm's own R&D increases through the additional benefits from exploiting spillovers, while lowering the *effective* spillovers. There is a cost to absorbing spillovers, so the effectiveness of rival R&D is reduced, whereas the effectiveness of own R&D increases by allowing a higher payoff.

In order to interpret $\delta$ as the difficulty of exploiting spillovers, assume usable rival R&D is decreasing in $\delta$.

$$\frac{\partial y}{\partial \delta} < 0.$$

The above implies that as the difficulty of exploiting spillovers increases, usable rival R&D falls, so assume also that absorptive capacity itself, $\frac{y}{X}$, also decreases in $\delta$.

$$\frac{\partial^2 y}{\partial \delta \partial X} \leq 0.$$

In addition, assume that as the difficulty of absorbing spillovers increases, the marginal rate of substitution between firm's own R&D and rival R&D is also decreasing in $\delta$, or that own R&D increases to produce usable rival R&D.

$$\frac{\partial(\frac{\partial y}{\partial X} / \frac{\partial y}{\partial x})}{\partial \delta} \leq 0.$$

Lastly, as usable R&D is decreasing in $\delta$, assume that this does not increase the extent of spillovers. This implies that although own R&D may increase to offset increased difficulty in absorbing spillovers and to produce usable rival R&D, the effectiveness of own R&D does not increase as the additional benefit own R&D generates through absorbing spillovers reduces.

$$\frac{\partial \beta}{\partial y} \geq 0.$$

# B Figures

Figure B1: Percentage of firms using external sources of information and cooperative arrangements BOS 2005-17 (Measurement variables for demand-pull absorptive capacity)

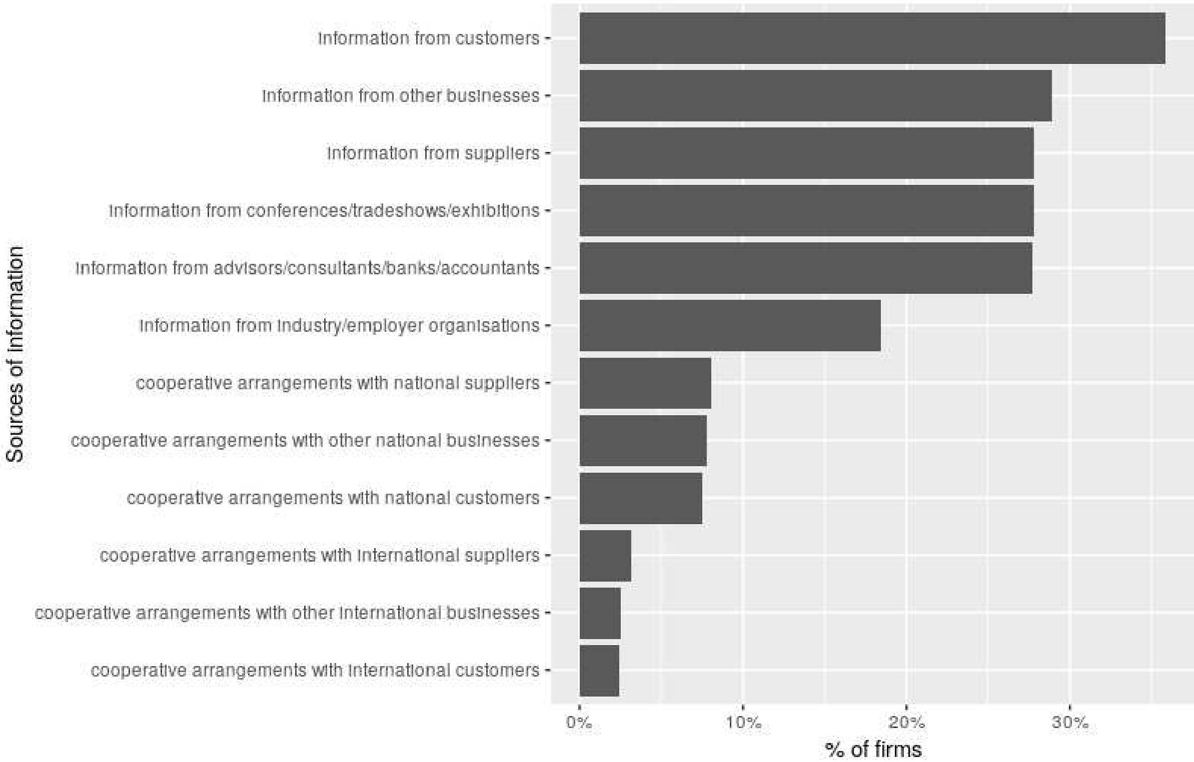


Figure B2: Percentage of firms using external sources of information and cooperative arrangements BOS 2005-17 (Measurement variables for science-push absorptive capacity)

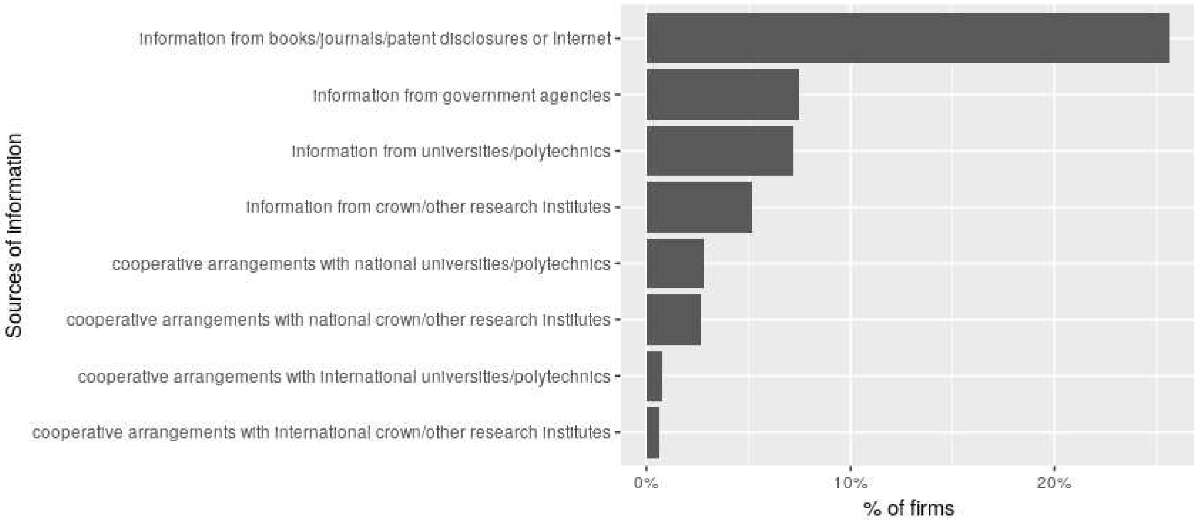



Figure B3: Percentage of firms performing innovation, R&D and export BOS 2005-17 (Measurement variables for overall absorptive capacity)

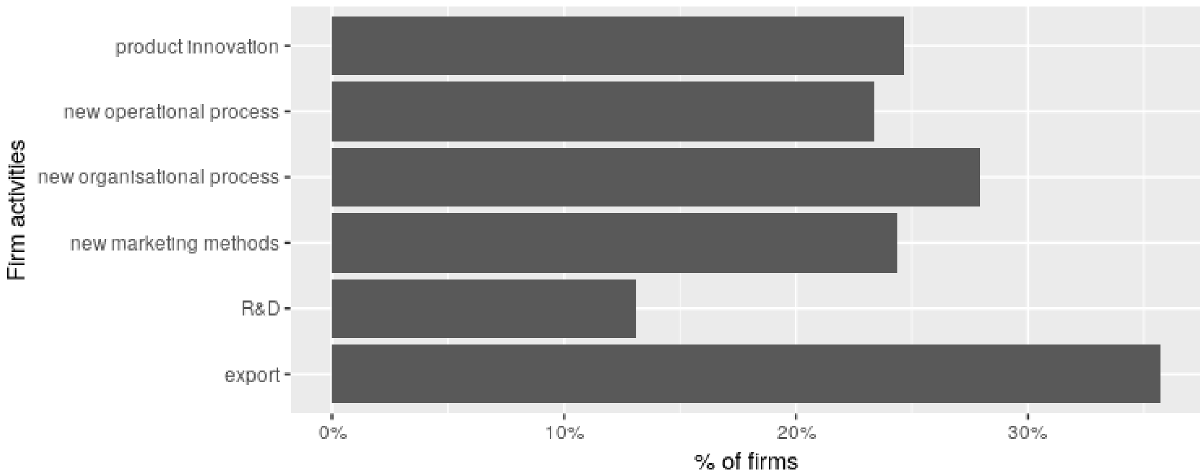


Figure B4: Demand-pull absorptive capacity for innovating and non-innovating firms by industry

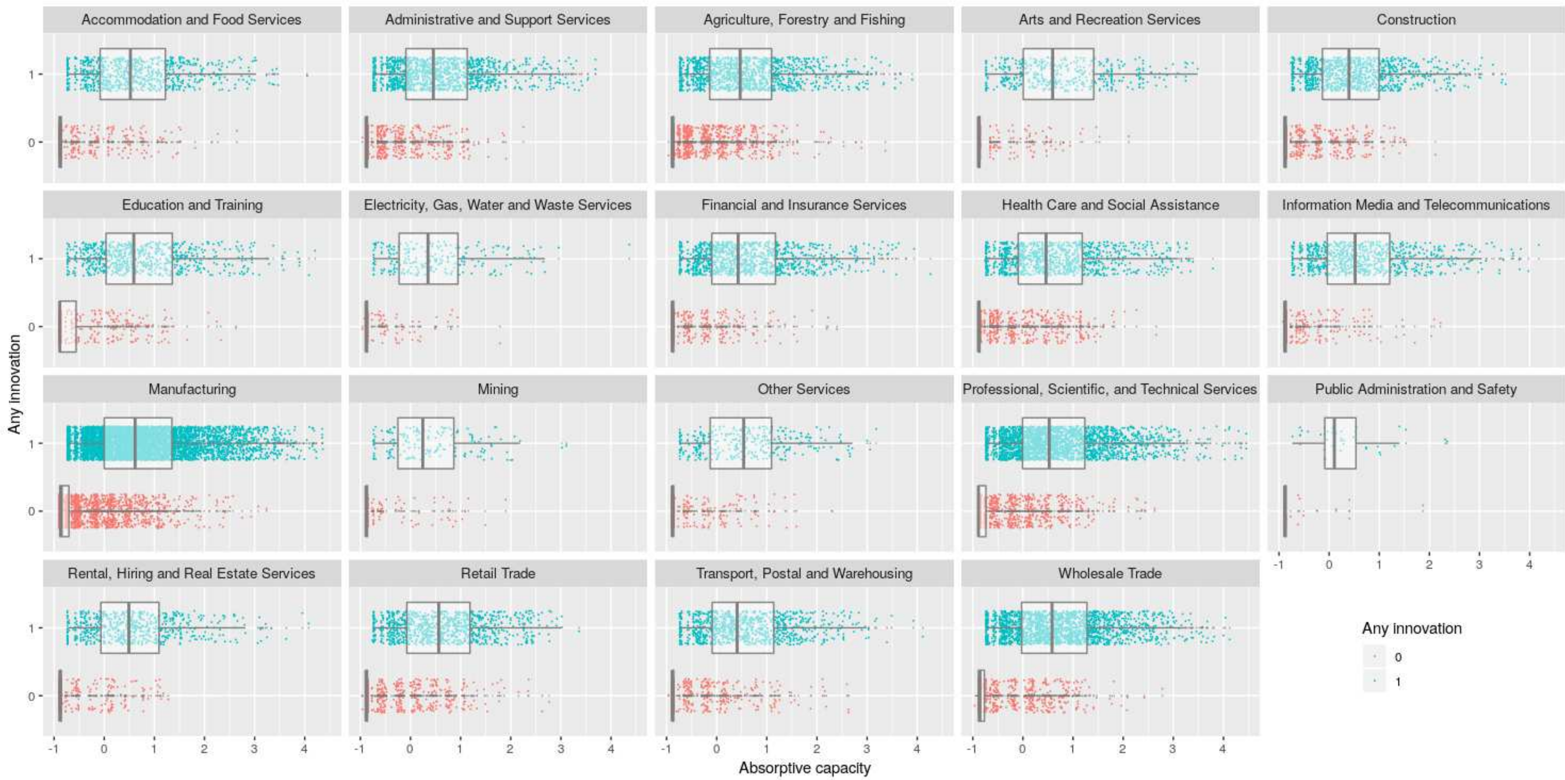


Figure B5: Science-push absorptive capacity for innovating and non-innovating firms by industry

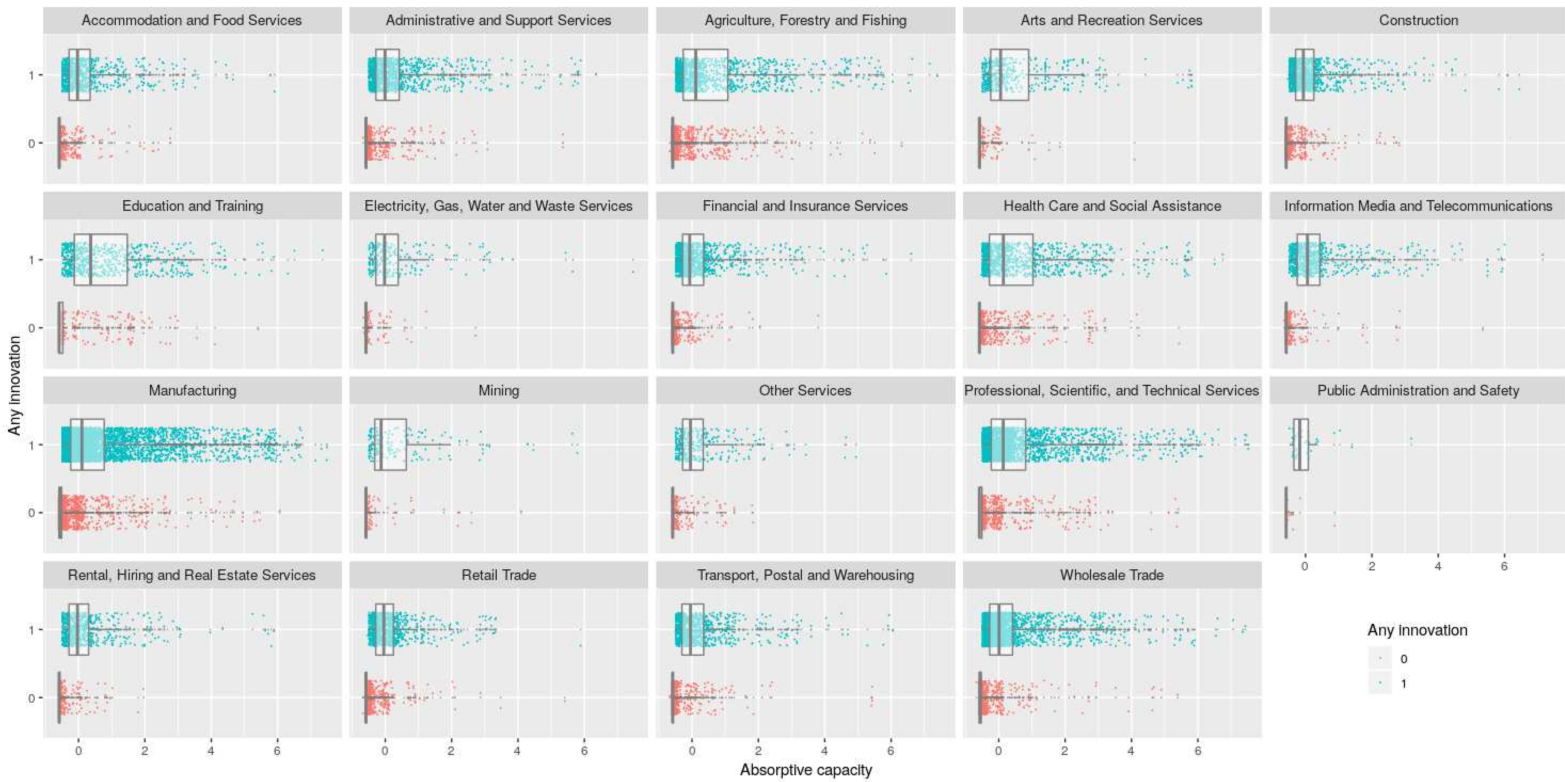


Figure B6: Median overall absorptive capacity by industry (standardised)

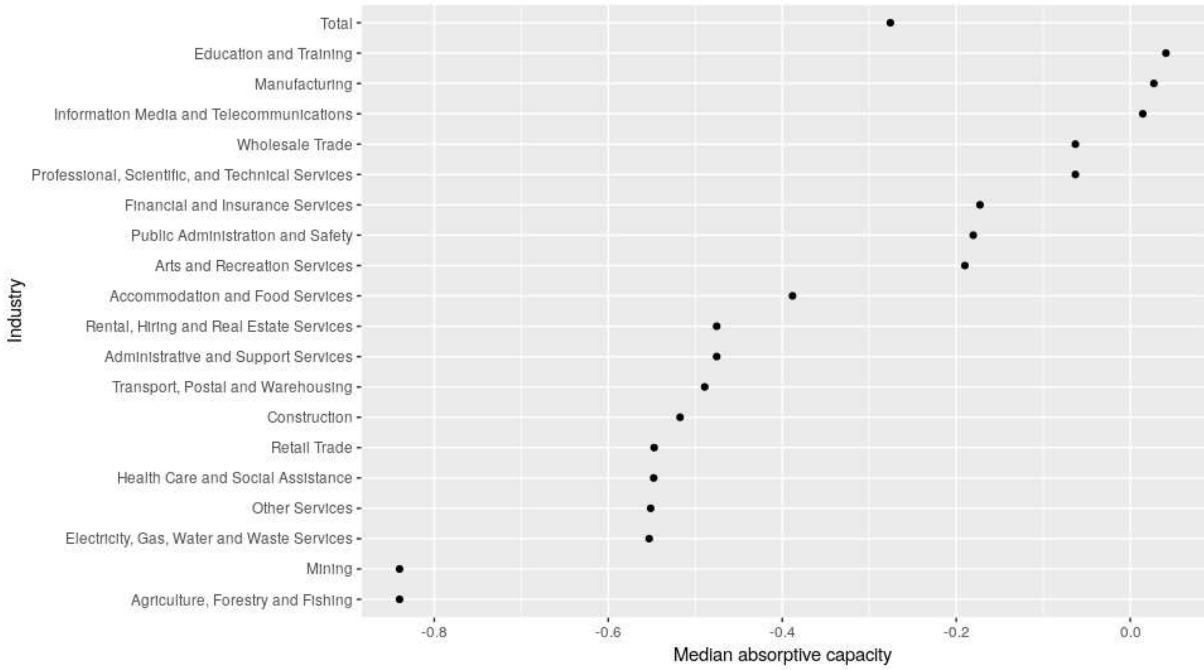



Figure B7: Kernel density plot of demand-pull, science-push and overall absorptive capacity