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External shocks and enterprises' dynamic capabilities in a time of regional distress

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Abstract

We study if dynamic capabilities alleviate enterprises' revenue losses after an external shock. Contextually, we study Norwegian enterprises before and after the price decline of crude oil in 2014, which strongly affected economic activities across industries in some regions, while others were practically unaffected. Empirically, we combine data of regional oil dependency and enterprise- and person-level data before the decline and enterprise-level revenues before and after the decline. Analyses of 4,060 enterprises in 51 labor market regions show that unrelated education diversity alleviates revenue losses for enterprises in strongly affected regions, while related education diversity has an opposite negative effect. R&D investments and innovation alter revenue growth, but as the effects are consistent across more or less affected regions, the concepts are static enterprise resources and not dynamic capabilities.

1 | INTRODUCTION

When the price of crude oil declined steeply in 2014, many Norwegian enterprises in affected regions experienced revenue losses due to their direct or indirect dependency on a commodity of much lower value than before the decline. Nonetheless, some enterprises may have been able to alleviate revenue losses due to their dynamic capabilities, which are the "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997, p. 516). The unexpected decline (Baumeister & Kilian, 2016) indicates "rapidly changing environments," as numerous enterprises became in need of alternative or complementary revenue streams. In this paper, we label the decline as an external shock or crisis for enterprises in affected regions and study if dynamic capabilities have enabled them to alleviate revenue losses.

Dynamic capabilities have been researched as means to cope with enterprises' challenges (Barreto, 2010; Eisenhardt & Martin, 2000; Laaksonen & Peltoniemi, 2018; Pisano, 2017; Salvato & Vassolo, 2018; Teece, 2018). Studies have also touched upon whether dynamic capabilities alleviate enterprises' negative consequences of an external shock (Ahn et al., 2018; Makkonen et al., 2014), but they have not investigated how the concepts are linked. Other research has highlighted how enterprises *respond* to an external shock or crisis (Wenzel et al., 2020), but we study if *pre*-crisis dynamic capabilities have alleviated revenue losses in the crisis' aftermath. Hence, we emphasize the performance *outcomes* of enterprises' dynamic capabilities (for a review also comprising other aspects of dynamic capabilities, see Schilke et al., 2018).

Teece (2007, 2020) argues that dynamic capabilities involve sensing, seizing, and transforming. Sensing "include[s] environmental scanning… from internal and external sources… [to] identify new opportunities such as underserved markets or supplemental revenue sources. …[It] requires an internal knowledge network built on decentralized authority, a collaborative organizational culture, and the ability to extract meaning from heterogenous signals" (Teece, 2020, p. 11). Seizing involves "the design or updating of business models for new products and services… [and] also encompasses allocating resources, including cash, to high-yield uses, or uses with the potential to become so." Transformation, or reconfiguration, implies that the enterprise periodically restructures "to maintain evolutionary fitness" by developing new structures, business models, products or services while abandoning other activities (ibid.).

In the next section, we identify concepts that reflect sensing, seizing, and transformation activities as building blocks of dynamic capabilities and analyze their performance effect when exposed to an external shock. There are no universally agreed upon measures of dynamic capabilities (Schilke et al., 2018), and our study's strength is to combine different types of data from different sources at different levels to assess different facets of the concept. Contextually, we study Norwegian enterprises before and after the price decline of crude oil in 2014, which strongly affected economic activities across industries in some regions, while others were practically unaffected. We access data that identify Norwegian labor market regions' *varying* dependency on the petroleum sector *before* the decline in 2014 (Vatne, 2013). Although research has examined external shocks (e.g., Lee, 2017; Tan et al., 2020), our approach is unique as we combine data on regional oil dependency and enterprise- and person-level data before the decline and enterprise-level revenues before and after the decline. Also, we access data on the enterprises' regional location according to their actual concentration of employment, which does not always correspond to the headquarters' location. As such, we research a unique natural experiment combining data from multiple sources at different levels. We analyze 4,060 enterprises in numerous industries in 51 (out of 89) Norwegian labor market regions. Our results show that unrelated education diversity alleviates revenue losses for enterprises in strongly affected regions, while related education diversity has an opposite negative effect. Also, R&D investments and innovation alter revenue growth, but the effects are consistent across more or less affected regions.

The study makes the following contributions: First, it emphasizes the core of Teece et al.'s (1997, p. 516) definition of dynamic capabilities to cope with "rapidly changing environments." For enterprises in regions exposed to the oil industry, the decline represented a perfect storm in terms of "rapidly changing environments" as they, almost overnight, became exposed to a very different market situation. Not only did the decline affect enterprises directly involved in the oil industry, but it further induced a negative shift in demand in many industries in the regional economy. Certain industries were affected more than others, but later we explain how the study controls for this. Schilke (2014) has illuminated how "environmental dynamism" moderates the association between dynamic capabilities and performance, but he relies on cross-sectional perceptual data and not an exogenous shock. Hence, ours is the first study to investigate if concepts reflecting sensing, seizing, and transformation enable enterprises to alleviate revenue losses after an external shock as an indicator of "environmental dynamism" or "rapidly changing environments."

Second, we compare enterprises in strongly affected regions with enterprises in less-affected regions. Such a comparison enables us to assess if supposed dynamic capabilities affect revenue growth differently for enterprises exposed to "rapidly changing environments" with those less exposed. If yes, the study provides genuine support to the framework of dynamic capabilities. If not, the study falsifies it. If supposed dynamic capabilities affect revenue growth, but the effect is insensitive to a location in more or less affected regions, the study furthermore distinguishes the framework as static, concurrent with the resource-based view (Barney, 1991; Barney et al., 2011; Penrose, 1959), and not as dynamic capabilities. In other words, if supposed dynamic capabilities have a positive effect on revenue growth but are not altered by location in regions more or less exposed to the external shock, they are insensitive to "rapidly changing environments." Accordingly, supposed dynamic capabilities can be labeled as static resources because they leverage revenue growth that is not influenced by a dynamic change in the environment.

We agree with Schilke et al. (2018, p. 406), stating that "dynamic capabilities can in principle exist and help firms compete in both relatively stable and highly dynamic [rapidly changing] environments." However, our study scrutinizes which indicators of sensing, seizing, and transformation affect revenues for enterprises located in regions exposed to a shock compared to those that are not. Brouthers et al. (2008) have examined how country-specific issues moderate the effect of dynamic capabilities on entry mode and performance, but their dependent variables are perceptual, and the cross-sectional design precludes the assessment of "rapidly changing environments." Parente et al. (2011) have examined cultural distance, which taps into the study of geography, but they too use perceptional indicators (except for firm size) in a cross-sectional design. Responding to these limitations, our study contributes to dynamic capability research as it increases the knowledge of the role of geography and rapidly changing environment in regions more or less exposed to an external shock.

The study has strong internal validity as it includes data on regional and enterprise-level characteristics before the decline and enterprise-level revenues before and after the decline. It stands in contrast to other studies analyzing dynamic capabilities in cross-sectional research designs (for a review, see Schilke et al., 2018), which contradicts the connotation of a "dynamic" concept.

Finally, the study has strong external validity as it covers more than 4,000 enterprises operating in numerous industries of numerous sizes and located in the majority of Norway's regions. Hence, it identifies enterprise-level concepts of dynamic capabilities that are generic and not idiosyncratically tailored to specific industries or enterprises of different sizes. Unless research rigorously identifies generic concepts, it puts the very paradigm under scrutiny in jeopardy, and our study avoids this pitfall.

2 | CONCEPTUAL MODEL AND ENTERPRISE-LEVEL DYNAMIC CAPABILITIES

The model in Figure 1 illustrates how enterprise-level constructs may moderate the association between a region-level construct and an enterprise-level outcome (for further readings, see Rousseau, 1985).

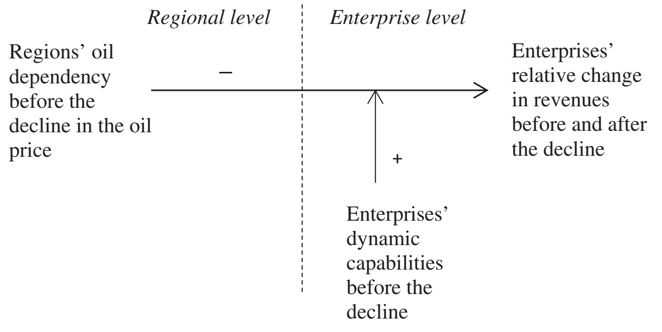

FIGURE 1 A conceptual multi-level model

It suggests that regional oil dependency harms enterprises' revenue growth after the crude oil price decline in 2014. Accordingly, a premise is that enterprises in oil-dependent regions have experienced weaker revenue growth than enterprises in less-affected regions. The model further indicates how enterprise-level dynamic capabilities have alleviated revenue losses for enterprises in oil-dependent regions.

In the following, we explain the enterprise-level concepts of R&D investments, education level, experience, diversity, innovation in the enterprise, and innovation collaboration with external partners as indicators of dynamic capabilities. Each reflects one or more of Teece's (2007, 2020) constructs of sensing, seizing, and transformation.

2.1 | R&D investments

R&D investments indicate analytical knowledge grounded in employees' scientific and codified skills (Asheim & Coenen, 2005). They further indicate absorptive capacity “to recognize the value of new, external information, assimilate it, and apply it to commercial ends” (Cohen & Levinthal, 1990, p. 128). Absorptive capacity capacitates “the acquisition of novel and valuable knowledge from external networks” (Parra-Requena et al., 2013, p. 157) and “helps in learning external sources of knowledge” (Yang & Lin, 2012, p. 333). R&D investments also increase enterprises' innovation performance (Aarstad & Kvitastein, 2019).

We assume that R&D investments, facilitating access to external knowledge, learning, and developing new innovative products and services, capacitate an enterprise to alleviate revenue losses after an unexpected external shock. External knowledge, learning, and the development of new innovative products and services are further in alignment with sensing, seizing, and transforming as they relate to “environmental scanning… from internal and external sources… [to] identify new opportunities,” “the ability to extract meaning from heterogenous signals,” “the design or updating of business models for new products and services,” and maintaining “evolutionary fitness” by developing new products or services (Teece, 2020, p. 11). Along these lines of reasoning, research indicates a positive link between R&D investments and dynamic capabilities in terms of sensing, seizing, and transformation (Babelytė-Labanauskė & Nedzinskas, 2017). Helfat (1997), similarly shows that R&D investments are a means to develop dynamic capabilities. We, therefore, suggest that R&D investments alleviate revenue losses for enterprises exposed to a sudden external shock.

2.2 | Education level

We have not identified research investigating the link between enterprise education level and dynamic capabilities, but other research shows that education level correlates with creativity (Ng & Feldman, 2009), innovation performance (Romero-Martinez et al., 2017), and organizational commitment (Ariffin & Ha, 2015). Coining these findings with sensing, seizing, and transformation, we reason that an enterprise with educated employees in response to an external shock is capable of scanning the internal and external environment, designing business models for new products, and restructuring to maintain "evolutionary fitness." We measure the employees' average level of education for each enterprise, and assume it capacitates an enterprise to alleviate revenue losses after an unexpected external shock.

2.3 | Experience

Employee experience encapsulates tacit and explicit knowledge, skills, and routines, along with internal and external network resources (Bell et al., 2011; Solheim & Herstad, 2018). Experience can be positive due to the knowledge, skills, routines, and network resources it reflects. However, it may also indicate outdated competence, decay or unlearning of previous knowledge, and an increasing inability to acquire new relevant skills (Solheim & Herstad, 2018).

Sturman (2003) researches employees' age and seniority as indicators of experience. In line with the arguments above, he alludes that experience up to a certain point positively affects employees' organizational performance but then turns negative. Consistent with Sturman, we analyze experience as a function of the employees' seniority and age and model it as a second-degree polynomial to assess a potential curvilinear effect.

Studies indicate that experience can act as a catalyst for dynamic capabilities (Zahra et al., 2006; Zollo & Winter, 2002), but research also shows mixed results (von den Driesch et al., 2015). As experience accumulates environmental scanning from internal and external sources (cf. sensing), it possibly enables an enterprise to alleviate an unexpected external shock's negative effects. Conversely, concerning the updating of business models for new products and services (cf. seizing) and restructuring "to maintain evolutionary fitness" (cf. transformation), experience likely precludes an enterprise from alleviating negative effects of an external shock. The reason is that experience, despite reflecting knowledge and rich access to internal and external networks, due to rigidities in an uncertain environment, is less responsive to rapidly changing challenges (Hamori & Koyuncu, 2015; Solheim & Herstad, 2018). Based on the two opposing arguments, we conclude that experience either alleviates or aggravates revenue losses for an enterprise facing an unexpected external shock.

2.4 | Diversity

Dynamic capability research has touched upon the concept of diversity (Drnevich & Kriauciunas, 2011; Helfat & Peteraf, 2015), and Døving and Gooderham (2008) show that diversity in human capital affects the scope of the services that accountancy firms provide. Diversity gives access to non-redundant information and resources, generating creativity and providing novel and innovative ideas (Burt, 1992, 2004). Roberson et al. (2017), nonetheless, concluded that findings are mixed concerning diversity's effect on organizational performance.

The mixed findings can have several explanations, and the first is that diversity possibly has a different effect on performance as a function of whether an enterprise is exposed to an external shock or not. In the absence of an external shock, there is a limited need to adapt to a novel situation, which implies that diversity possibly has a limited effect on performance, at least in the shorter run (March, 1991; Osiyevskyy et al., 2020). Diversity may even hamper performance as exposure to various stimuli from different sources can preclude the execution of efficient operations. The economic geography literature has debated the potential benefits of a diversified regional industry structure (Aarstad & Kvitastein, 2019; Beaudry & Schiffauerova, 2009), and there is empirical evidence indicating that it hampers productivity (Aarstad et al., 2016b). Other research shows that diversity increases radical innovation performance (Castaldi et al., 2015) and induces sectorial reorganization after an external shock (Lee, 2017). Drawing upon these studies, we assume that diversity is positive when facing a situation where day-to-day routine-based operations requiring limited novel information no longer suffice to leverage a steady revenue stream, while it can be negative in the absence of such a situation.

The second reason for inconclusive research is that diversity is a multidimensional concept. Different types of diversity may have different performance effects, and we account for the issue by including various measures of the concept. We study diversity in formal education levels as employees with higher-level education have other skills than colleagues with less formal education. Employees with different education levels probably also have different interpersonal networks. Also, we study diversity in experience as experienced employees have informal, often tacit, skills and knowledge, while their less experienced peers may have better digital competence. Diversity in experience can furthermore induce diversity in interpersonal networks, but which do not necessarily overlap with network ties related to the employees' formal level of education. Altogether, we assume that diversity in formal education level and experience reflects different concept dimensions.

The third reason for inconclusive research is that diversity can be related and unrelated. For instance, if the employees' educational background in one enterprise shares many similarities, the diversity is related, and if the employees' educational background in another enterprise shares few similarities, the diversity is unrelated. Solheim et al. (2020) show that related diversity, or variety, concerning employees' industry background, increases enterprises' incremental innovation performance while unrelated diversity, or variety, increases radical innovation performance. A probable reason why related diversity increases incremental innovation performance is that overlapping complementary cognitive models among employees sharing many similarities enables them to develop novel and improved solutions to improve daily operations. Related diversity, therefore, is likely beneficial in a context absent of an external shock as the market situation is stable and does not require any radical shift in the enterprises' activities.

On the other hand, unrelated diversity is probably more beneficial when facing an external shock as it reflects a combination of very different cognitive models or perspectives, enabling the enterprise to develop strategies for alternative or complementary revenue streams. We study related and unrelated diversity in employees' educational backgrounds and assume that related diversity is beneficial in the absence of an external shock but less so in one's presence. Concerning unrelated diversity in educational background, we divergently assume that it is positive in the presence of an external shock but less so in the absence of one.

We conclude that diversity, including unrelated but not related diversity, is positive for an enterprise facing an external shock. The reason is that diversity reflects different cognitive models providing access to non-redundant information and resources in a situation where day-to-day routine-based operations no longer suffice to leverage a steady revenue stream. Diversity taps into sensing and transformation as it enables "environmental scanning… from internal and external sources…" and further increases the "the ability to extract meaning from heterogenous signals…" as crucial means to periodically restructure the enterprise "to maintain evolutionary fitness" (Teece, 2020, p. 11).

2.5 | Innovation

Schoemaker et al. (2018, pp. 17–18) argue that "[d]ynamic capabilities are about doing the right things at the right time, based on new product (and process) development, unique managerial orchestration processes, a strong and change-oriented organizational culture, and a prescient assessment of the business environment and technological opportunities." Their statement implies that dynamic capabilities and innovation are intertwined constructs, and other scholars indicate a similar link (Rothaermel & Hess, 2007; Salunke et al., 2011; Verona & Ravasi, 2003). Other research emphasizes that an enterprise's external links affect innovation performance and even complement or substitute for R&D investments (Aarstad et al., 2019). A likely reason, according to Dyer and Singh (1998, p. 665), is that "a firm's alliance partners are, in many cases, the most important source of new ideas and information that result in performance-enhancing technology and innovations." Gulati (1998, p. 296) likewise asserts that alliance partners "develop a shared understanding of the utility of certain behavior due to discussing opinions in strong, socializing relations, which in turn influence their actions." In a literature review, Mamedio et al. (2019, p. 83) affirm that strategic alliances are a flexible vehicle for learning, an efficient knowledge transfer mechanism between firms, and "a superior means of access to technological capabilities and other complex capabilities." Consistent with these studies, we conclude that if exposed to an external shock, innovation in the enterprise and innovation collaboration with external partners alleviate revenue losses as such activities reflect internal and external scanning, the updating of business models for new products and services, and restructuring "to maintain evolutionary fitness" (Teece, 2020, p. 11).

2.6 | Concluding table

Table 1 concludes the suggested alleviating effects R&D investments, education level, experience, diversity, innovation in the enterprise, and innovation collaboration with external partners have on revenue losses for enterprises facing an external shock. It also includes a column showing significant empirical results. Finally, it includes a column showing significant direct effects on revenue growth independent of whether the enterprise is in a region strongly exposed to the external shock or not.

TABLE 1 Suggested alleviating effects, empirical alleviating effects, and empirical direct effects on the dependent variable

Concept	Suggested alleviating effect	Empirical alleviating effect	Empirical direct effect
R&D investments	+		+
Average education level	+	(−)	
Average experience	+/−		∩
Diversity in education level	+		+
Diversity in experience	+		−
Unrelated education diversity	+	+	−
Related education diversity	−	−	
Innovation in the enterprise	+		+
Innovation collaboration regionally, nationally, and internationally	+		

3 | METHODOLOGY

3.1 | Merging different datasets

Our primary data source at an enterprise level is the Community Innovation Survey of 2012 by Statistics Norway (Wilhelmsen & Berrios, 2015). Participation is mandatory, eliminating non-respondent bias, and the survey includes data on enterprises operating in most industries in all labor market regions of the country. All enterprises of at least 50 employees are surveyed, and for those with 5–49 employees, randomized strata of different sizes are surveyed. The 2012 survey includes 6,271 enterprises. It reports the regional location of each enterprise, which for multiunit enterprises is the headquarter's location. However, as the headquarter's location does not always correspond with the actual concentration of employment, we use person-level data of 2012 linked with enterprise employment data and data identifying the labor market region where each employee is working to count the number of employees in different labor market regions for each enterprise. Next, we define the mode region of employment as the enterprise's de facto location, the labor market region where most of the enterprise's employees work. All person-level data include full-time employees only.

The person-level data of 2012 further include information on each employee's education level, type of education, age, and the number of years since the person graduated from the highest level of education taken. Aggregating this data to an enterprise level enables us to model average education level, experience, and different forms of diversity. From another dataset, we access data on each enterprise's operating revenues in 2012 and 2016 to model revenue growth as the dependent variable.

3.2 | Revenue growth as a dependent variable

We model the dependent variable, revenue growth, as the relative change in each enterprise's operating revenues before and after the decline, as follows: ((Operating revenues in 2016)—Operating revenues in 2012)/Operating revenues in 2012 (accounting for the consumer price index does not substantially affect the regression results as it percentagewise equally deflates the value of all observations minus the constant of one). Revenue growth deviated from a normal distribution at the outset, but as it includes negative values, we cannot log-transform it (Operating revenues in 2016 divided by Operating revenues in 2012 does not take negative values, but when log-transforming the expression in an unreported analysis, it deviated from a normal distribution.) Instead, we apply Van der Waerden's (1953) transformation approach, $S = \phi\left(\frac{i}{n+1}\right)$. S is the normal score approximation for a given observation, i is its rank, n is the number of observations, 4,060, and ϕ is the inverse cumulative standard normal distribution. The approach's properties are investigated concerning usefulness (e.g., Hallin & Mélard, 1988; Hallin & Paindaveine, 2004) and theoretical properties (Orban & Wolfe, 1982). The method ensures that parametric tests' normality assumptions are satisfied while simultaneously resembling the original untransformed data. After transforming the variable, the skewness and kurtosis are practically zero.

3.3 | Region-level oil dependency as an independent variable

Statistics Norway divides the country into 89 labor market regions. Vatne (2013), in his assessment of regional oil dependency, first maps enterprises in industries according to NACE-codes that tailor products to the petroleum sector and that are not likely tradable beyond it. Subsequently, he interviews mapped enterprises to assess the percentage of sales to the petroleum sector. If the enterprise's or a subunit's sales are below 20%, they are omitted from the data. “It is particularly important to map all Norwegian subunits where the enterprise is operating. Based on this information, we estimate how many employees in each unit are employed with petroleum specific activities and in which region this work is carried out” (our translation of Vatne, 2013, p. 13). The data includes 1,694 enterprises with a total number of 2,464 subunits. About 35% of the enterprises have less than ten employees. Vatne calculates that about 125,500 employees in these enterprises and their subunits are directly employed with petroleum-specific activities. To calculate each labor market region's oil dependency, he divides the number of employees directly employed with petroleum-specific activities by the total private sector employment in the region. Labor market regions with less than 50 employees or less than three enterprises involved with petroleum-specific activities are excluded. Altogether, Vatne estimates oil dependency in 51 out of 89 labor market regions. The maximum regional oil dependency is 21.8%, and the minimum dependency is 0.15%.

We emphasize that a region's oil dependency is constant for all enterprises independent of the industry they operate in. When the crude oil price fell, enterprises in oil-dependent regions operating in many industries, also beyond petroleum-related industries, were affected as the decline induced a fall in demand in the overall regional economy. Granted, some industries in oil-dependent regions were affected more than others, but later we explain how the study controls for industry-specific effects.

Figure 2 illustrates that the crude oil price decline in 2014 was steep and sudden. Also, it illustrates that the price since then, albeit periodically increasing somewhat, by far has returned to previous levels (the price development after 2016 is not relevant concerning the data in this study, but we include it as it may be of general interest). In addition, Figure 2 shows that the price was about 20USD per barrel in nominal terms until it started to increase in 2001. The decline in 2008 was due to the financial crisis, but the price quickly bounced back in 2011. Since then, it was stable at a high level till it declined in 2014.

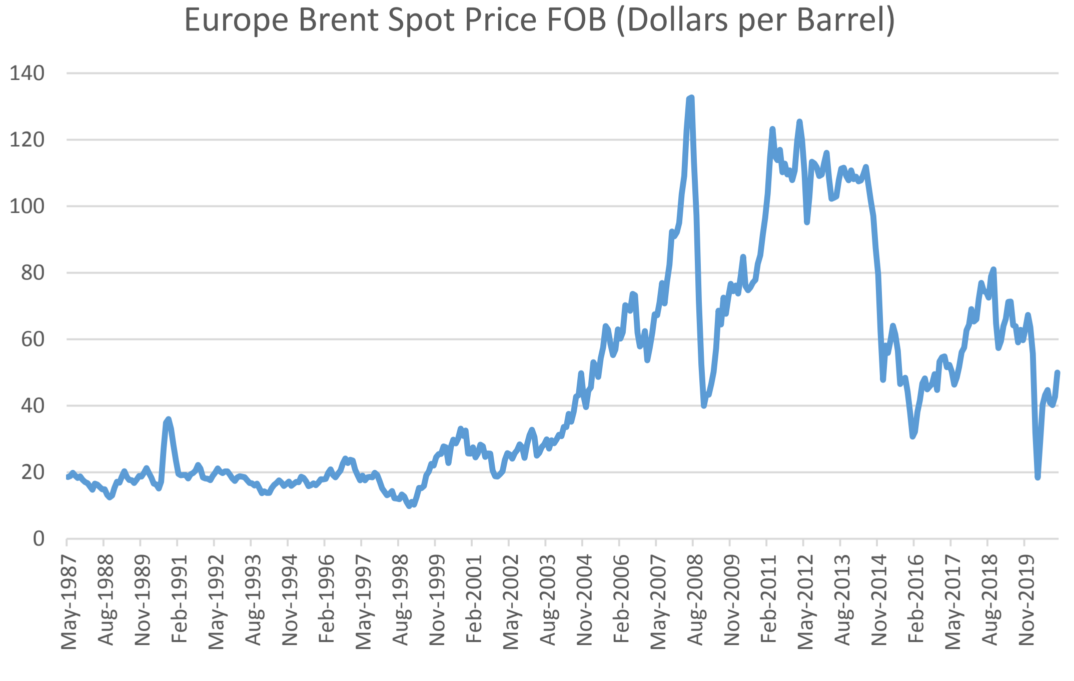

FIGURE 2 Monthly development in nominal USD for the spot price per barrel of Brent oil

3.4 | Enterprise-level independent variables

3.4.1 | R&D investments

The Community Innovation Survey provides data about enterprises' R&D investments in 2012. We divide the measure by the number of employees as an indicator of R&D intensity.

3.4.2 | Average education level

The person-level data includes information about each employee's education level following the Statistics Norway classification (https://www.ssb.no/en/klass/klassifikasjoner/36/). Education level varies from zero (no education and pre-school education) to eight (second-stage tertiary education/postgraduate education). For each enterprise, we use person-level data to measure the average education level.

3.4.3 | Average experience

First, we use the person-level data of year of birth for each employee to model the average age in 2012 and standardize the indicator. Second, we use the person-level data to estimate the number of years since each employee finished the highest education level taken no later than 2012 as an indicator of seniority. We model average seniority and standardize the indicator. To model average experience, we take the average of the standardized average of age and seniority.

3.4.4 | Diversity in education level

To model diversity in education level, we take the standard deviation measure of employees' education level in each enterprise.

3.4.5 | Diversity in experience

To model diversity in experience, we follow a similar procedure as for average experience but include standard deviation measures (instead of average measures).

3.4.6 | Unrelated education diversity

The person-level data also includes data on education type, which follows a five-digit hierarchy (similar to the hierarchy and classification of NACE-codes to identify in which industry enterprises operate). To model unrelated education diversity, we use the digit-one hierarchy, which, for instance, distinguishes employment background in (1) business administration and (2) natural sciences, vocational, and technical subjects. There are ten different education groups within the digit-one hierarchy (see https://www.ssb.no/en/klass/klassifikasjoner/36/). We use Shannon's (1948a, 1948b) entropy formula to measure enterprise unrelated education diversity, $\mathrm{UED} = \sum_{k=1}^{n} s_{ge} \ln\left(\frac{1}{s_{ge}}\right)$, where s_{ge} is the proportion of employees in education group g in enterprise e. If $s_{ge} = 0$, then $\ln(1/S_{ge}) = 0$; n is the number of identified education groups.

3.4.7 | Related education diversity

To measure related education diversity, RED, we use a similar approach but instead apply the digit-five hierarchy, making the finest distinction between different education groups. Next, we subtract the UED measure to "take out" the effect of diversity between different education groups. The RED measure indicates diversity between similar education groups (while UED indicates diversity between different education groups). An analog approach is used to measure regional industry structures' unrelated and related diversity (Aarstad et al., 2016c).

3.4.8 | Innovation in the enterprise

To map innovation in the enterprise, the Community Innovation Survey asks (our translation from Norwegian): How important was the following in 2010–2012 for the development of new products or services: (1) extending the spectrum of goods or services, (2) replacing outdated products or services, (3) penetrating new markets or increasing the market share, (4) improving the quality of products or services, (4) improving the flexibility of production of goods or services, (5) increasing capacity for the production of new goods or services, (6) reducing costs of work per unit produced, (7) reducing material and energy costs per unit produced, (8) reducing environmental effects, (9) improving employees' health and security. For each item, the respondent could indicate very important (coded 3), somewhat important (coded 2), of little importance (coded 1), or not relevant (coded 0). We take the items' average score to model the variable.

3.4.9 | Innovation collaboration

The Community Innovation Survey asks whether the enterprise between 2010 and 2012 had innovation collaboration with one or more enterprises/institutions in different geographical locations. If the enterprise reports one or more collaborations regionally, we code it as a dummy indicator of regional innovation collaboration (1 = yes; 0 = no) and follow a similar approach to model innovation collaboration nationally beyond the region and internationally. Research shows that innovation collaboration regionally, nationally, and internationally has distinct effects on innovation performance (Aarstad et al., 2016a, 2019).

3.5 | Enterprise-level control variables

We control for (1) enterprise size in the number of employees in 2012 and (2) a dummy reporting if the major market is in the region of location (default), domestically outside of the region, in Europe, or internationally beyond Europe. Also, we control for (3) operating revenues per employee in 2012 as an indicator of productivity.

3.6 | Econometric modeling and controlling for industry and regional effects

We use a multi-level mixed-effects random intercept linear regression model,

$$Y_{eir} = \sum_{h=1}^{n} \beta_h x_{heir} + E_{eir} + \beta_{0ir} + \beta_{0r}. \tag{1}$$

Y_{eir} is the dependent variable, revenue growth, for enterprise e in industry i (digit-two NACE-code) in labor market region r. $\sum_{h=1}^{n} \beta_h x_{heir}$ is the regression coefficient concerning each independent variable h for enterprise e in industry i in labor market region r. The regression coefficients are fixed effects (but must not be confounded with fixed effect cluster dummies). E_{eir} is the enterprise (level-one) residual (or error term). β_{0ir} is the intercept in industry i in labor market region r, and β_{0r} is the intercept in region r. Assuming that β_{0ir} and β_{0r} follow a normal distribution, they encompass the overall mean intercept β_0 plus the cluster-specific random intercepts I_{0ir} (operating in a specific industry in a specific region) and R_{0r} (operating in a specific region), hence

$$\beta_{0ir} + \beta_{0r} = \beta_0 + I_{0ir} + R_{0r}. \tag{2}$$

Substituting (2) into (1) gives

$$Y_{eir} = \beta_0 + \sum_{h=1}^{n} \beta_h x_{heir} + E_{eir} + I_{0ir} + R_{0r}.$$

The random intercepts effects account for operating in a specific region (R_{0r}) and operating in a specific industry in a specific region (I_{0ir}). (For further readings, see, e.g., Raudenbush & Bryk, 2002; Snijders, 2011.)

To ease comparisons, we standardize the continuous variables. Standardized variables are also mean-centered, which reduces potential challenges concerning multicollinearity when modeling interaction and polynomial terms (Cronbach, 1987). We analyze the model in Stata 14 (StataCorp., 2017).

4 | RESULTS

4.1 | General model presentations and model fit assessments of interaction terms

The final sample includes 4,060 enterprises in 51 different labor market regions. Model 1 in Table 2 includes as fixed effects regression estimators (1) oil dependency at a regional level, (2) enterprise-level independent variables, and (3) control variables. Random effects are nested industry and region effects. Model 2 adds interaction terms between dynamic capability indicators and regional oil dependency. Model 3 excludes non-significant interaction terms, and Model 4 further excludes non-significant independent and control variables. Likelihood ratio (LR) tests show that Models 2 and 3 have a significantly stronger model fit than Model 1. It implies that one or more interaction terms significantly improve the model fit. All fixed-effects variables are consistent in effect size and standard error across models.

TABLE 2 Multi-level mixed-effects random intercept linear regressions

	Model 1	Model 2	Model 3	Model 4
FIXED EFFECTS				
Intercept	.020 (.027)	.021 (.027)	.021 (.027)	.022 (.026)
Regional level				
Reg. oil dep. (ROD)	−.086 (.018)***	−.096 (.023)***	−.089 (.019)***	−.089 (.019)***
Firm level				
Potential dynamic capabilities				
R&D investments (R&D)	.095 (.018)***	.090 (.018)***	.097 (.018)***	.094 (.017)***
Av. ed. level (AEL)	−.009 (.019)	−.012 (.019)	−.013 (.019)	−.012 (.019)
Av. experience (AE)	−.113 (.016)***	−.112 (.016)***	−.113 (.016)***	−.113 (.016)***
AE × AE	−.027 (.011)*	−.026 (.011)*	−.027 (.011)*	−.027 (.011)*
Div. ed. level (DEL)	.035 (.017)*	.034 (.017)*	.035 (.017)*	.035 (.017)*
Div. experience (DE)	−.077 (.017)***	−.081 (.017)***	−.080 (.017)***	−.080 (.017)***
Unrel. ed. div. type (UED)	−.048 (.018)**	−.045 (.018)*	−.046 (.018)*	−.047 (.018)*
Rel. ed. div. type (RED)	−.023 (.017)	−.023 (.017)	−.022 (.017)	−.023 (.017)
Innovation (IN)	.041 (.017)*	.043 (.017)*	.042 (.017)*	.041 (.017)*
Reg. innov. collab. (RIC)	.092 (.068)	.087 (.068)	.084 (.068)	
Nat. innov. collab. (NIC)	−.018 (.077)	−.008 (.078)	−.015 (.077)	
Int. innov. collab. (IIC)	−.080 (.079)	−.081 (.079)	−.081 (.079)	
Controls				
Size in employees	−.006 (.016)	−.004 (.016)	−.002 (.016)	
National mrkt.	−.019 (.036)	−.018 (.036)	−.018 (.036)	−.019 (.036)
European mrkt.	.106 (.066)	.110 (.066)†	.110 (.066)†	.107 (.065)
Int. mrkt.	.041 (.064)	.041 (.064)	.046 (.064)	.040 (.063)
Rev. per empl. in 2012	−.057 (.016)***	−.056 (.016)***	−.056 (.016)***	−.056 (.016)***
Interactions				
R&D × ROD		.016 (.014)		
AEL × ROD		−.039 (.019)*	−.032 (.017)†	−.032 (.017)†
AE × ROD		.015 (.017)		
AE × AE × ROD		.009 (.012)		
DEL × ROD		.022 (.018)		
DE × ROD		−.008 (.018)		
UED × ROD		.054 (.019)***	.060 (.017)***	.060 (.017)***
RED × ROD		−.049 (.016)**	−.050 (.015)**	−.051 (.015)**
IN × ROD		.016 (.017)		
RIC × ROD		−.058 (.073)		
NIC × ROD		−.021 (.076)		
IIC × ROD		.092 (.079)		
RANDOM EFFECTS				
Residual	.919 (.022)	.914 (.022)	.918 (.022)	.919 (.022)

(Continues)

TABLE 2 (Continued)

	Model 1	Model 2	Model 3	Model 4
Nested industry effect	.033 (.012)	.029 (.012)	.027 (.012)	.026 (.012)
Region effect	6.83e−9 (2.79e−6)	.001 (.003)	.001 (.003)	.001 (.003)
Wald χ^2	202.8***	232.6***	222.9***	220.4***
Log likelihood	−5648.1	−5633.5	−5638.1	−5639.2
Likelihood ratio (LR) χ^2	12.5**	9.34**	8.49*	8.29*
Maximum/average VIF	2.18/1.34	2.44/1.46	2.18/1.31	1.39/1.19
LR test vs. Model 1: χ^2		29.2**	19.9***	

Note: Dependent variable: Revenue growth. Number of enterprises is 4,060. Number of regions is 51. Number of industries nested in regions is 1,081. We report standard errors in parentheses, and for fixed effects, we report conservative two-tailed tests of significance.

†$p < .10$

*$p < .05$; **$p < .01$; ***$p < .001$.

4.2 | Ruling out multicollinearity and assessing overall model fit

Maximum and average variance inflation factors (VIFs) are not critically high. The values are particularly low in Model 4, which rules out potential multicollinearity (O'Brien, 2007). Significant likelihood ratio (LR) χ^2 in all models informs about genuine random effects; the nested industry effect in all models is more than twice as high as the corresponding standard error. Significant Wald χ^2 in all models informs about robust model fit.

4.3 | Specific regression estimates

In line with the study's premise, regional oil dependency has a negative effect on revenue growth. The interaction term between unrelated education diversity and regional oil dependency (UED × ROD) has a significant positive effect on revenue growth, and the interaction term between related education diversity and regional oil dependency (RED × ROD) has a significant negative effect. Average marginal effects in Figure 3 are based on Model 4. They show that a one standard deviation increase in unrelated education diversity increases revenue growth by about .13 standard deviations in a region of maximum oil dependency, but it decreases revenue growth by about .10 standard deviations in a region of minimum oil dependency. In other words, unrelated education diversity increasingly alleviates revenue losses as regional oil dependency increases, but the effect is negative in a region of minimum oil dependency. Figure 3 further shows that a one standard deviation increase in related education diversity decreases revenue growth by about .17 standard deviations in a region of maximum oil dependency, but the effect is non-significant in a region of minimum oil dependency. Thus, related education diversity increasingly aggravates revenue losses as regional oil dependency increases, but the effect is non-significant in a region of minimum oil dependency.

The interaction term between average education level and regional oil dependency has a significant negative effect on revenue growth in Model 2 and borderline significant effects in Models 3 and 4. The average marginal effects in Figure 4 are based on Model 4. They show that an increase of one standard deviation in average education level decreases revenue growth by a little more than .10 standard deviations in a region of maximum oil dependency. Thus, the average education level increasingly

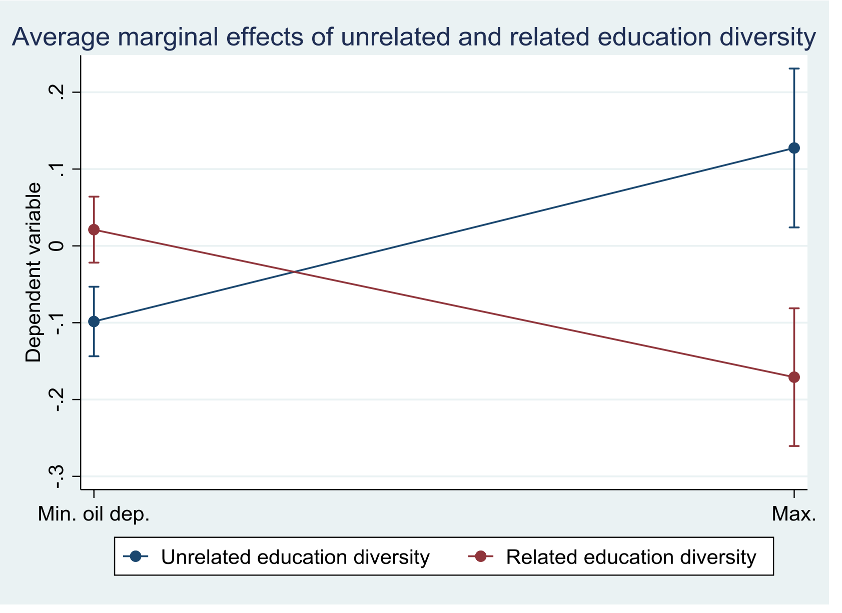

FIGURE 3 Average marginal effects of unrelated education diversity (blue line) and related education diversity (red line) as a function of increasing regional oil dependency (minimum oil dependency in the left part of the graph and maximum dependency in the right part). 95% confidence intervals in brackets. The calculation is based on estimates in Model 4

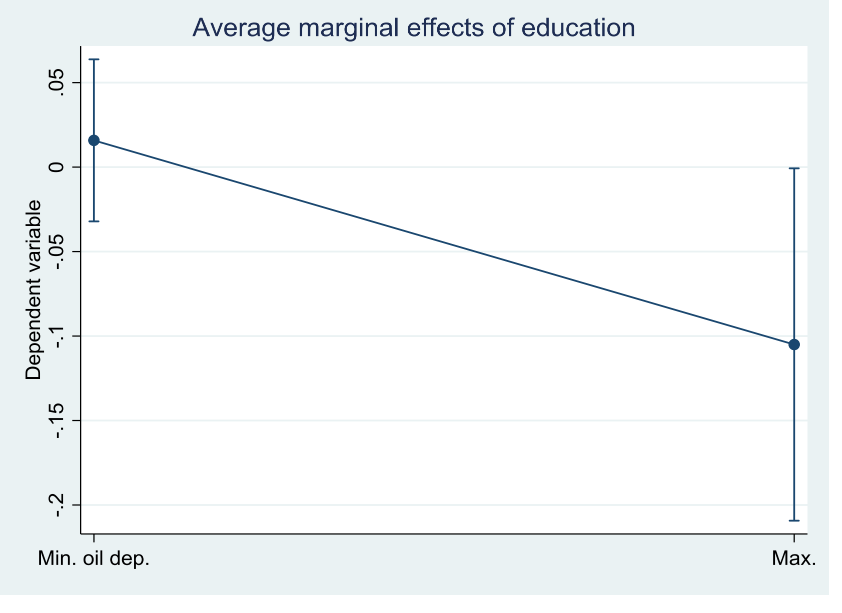

FIGURE 4 Average marginal effects of education level as a function of increasing regional oil dependency (minimum oil dependency in the left part of the graph and maximum dependency in the right part). 95% confidence intervals in brackets. The calculation is based on estimates in Model 4

aggravates revenue losses as regional oil dependency increases, but the effect is borderline significant. The effect is, moreover, non-significant in a region of minimum oil dependency.

The other interaction terms are non-significant, but Table 2 shows that some enterprise-level parameters have significant direct effects on revenue growth. Significant effects of enterprise-level parameters coined with non-significant interaction terms imply that enterprise-level effects are consistent, independent of being in a region exposed to an external shock or not. Enterprise R&D investments increase revenue growth. Average experience decreases revenue growth, and the significant second-degree polynomial further indicates that the effect on revenue growth decreases at an increasing rate. The effects in Figure 5 are based on Model 4. They show that increasing average experience from a very low to a moderate level increases revenue growth slightly, but beyond that, it decreases revenue growth at an increasing rate.

Diversity in education level has a positive effect on revenue growth, while diversity in experience has a negative effect. Innovating enterprises increase revenue growth, while operating revenues per employee in 2012, as an indicator of productivity, has a negative effect. The latter finding may be attributed to a "regression towards the mean" effect as high revenues in 2012 will tend to be lower in a later period, and vice versa.

So far, we have applied random intercept models, which do not permit correlation between the random effects. To ease this restriction, in unreported analyses, we replicated Model 4 by permitting a random slope on each significant independent variable (alone standing or part of an interaction term) at a time, that is, an unstructured covariance structure between the random intercept and the random slope on each variable. These are so-called random slope models (in contrast to random intercept models) as the unstructured covariance structure permits correlation between the random effects (for a detailed explanation, see Monsalves et al., 2020). However, no statistical conclusion was altered, and upon request, we can provide numeric details.

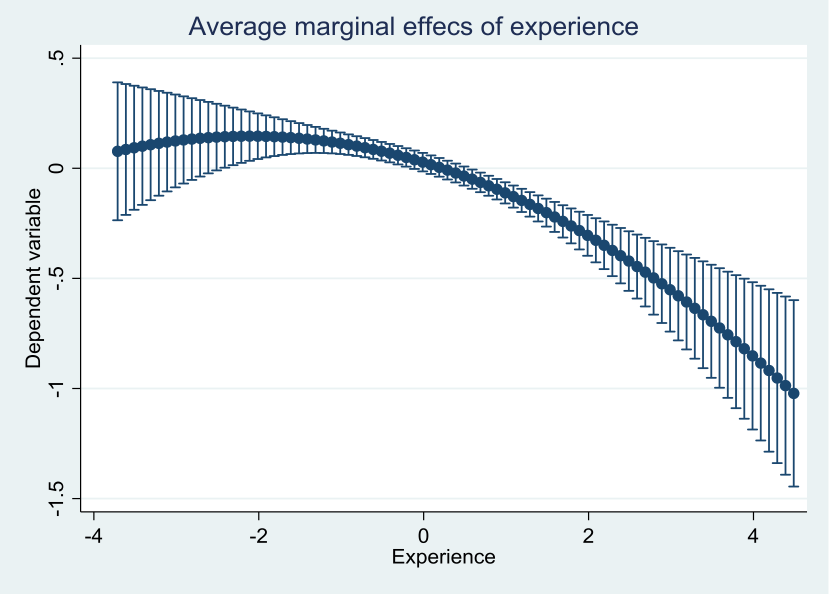

FIGURE 5 Average marginal effects of experience reporting standardized values. 95% confidence intervals in brackets. The calculation is based on estimates reported in Model 4

5 | CONCLUSION

5.1 | Discussion of the findings

A major finding is that for enterprises in regions strongly affected by the decline, unrelated education diversity alleviates revenue losses, while the effect is oppositely negative in less-affected regions. A probable explanation is that unrelated education diversity, when facing an external shock, induces a combination of very different cognitive models or perspectives, enabling the enterprise to develop strategies for alternative or complementary revenue streams (Solheim & Herstad, 2018). On the other hand, in the absence of an external shock, unrelated education diversity appears to hamper efficiency gains in a context where enterprises have limited needs to adjust course in the pursuit of generating revenues.

Second, related education diversity, in contrast to unrelated education diversity, aggravates revenue losses for enterprises in regions strongly affected by the decline. A probable explanation is that, when facing an external shock, related diversity in educational background does not suffice to induce complementary in cognitive models to develop strategies for alternative or complementary revenue streams. When facing an external shock of no clear-cut and predefined solution, related education diversity may further trigger conflicting interests, including role conflicts, among employees having very similar, albeit slightly different educational backgrounds.

Third, increasing average education level hampers revenue growth for enterprises in regions strongly affected by the decline. Albeit not robustly significant, the finding is perhaps surprising and counterintuitive, but a probable explanation is that a highly educated workforce is more rigid and reluctant to adapt to a new external reality and work environment than less-educated employees.

Fourth, it is worth noting that the interaction terms that include R&D investments, average experience, and internal and external innovation activities show non-significant revenue growth effects. A possible explanation is that these dynamic capabilities candidates play no genuine roles in alleviating revenue losses for enterprises facing an external shock. Instead, they may play an important role when facing other external challenges and may also play an important role concerning other performance measures after a crisis.

Fifth, albeit the interaction terms including R&D investments, average experience, diversity in education level and experience, and innovation show non-significant effects, the parameters have significant direct effects on revenue growth. Non-significant effects of interaction terms coined with significant direct effects of enterprise-level parameters imply that the enterprise-level effects are consistent, independent of being in a region exposed to an external shock or not. Since the concepts' effects are static and insensitive to "rapidly changing environments" (Teece et al., 1997, p. 516), we label them as enterprise *resources* (or *liabilities* if negative), concurrent with the resource-based approach (Barney, 1991; Barney et al., 2011; Penrose, 1959), and not as dynamic capabilities.

Finding that R&D investments increase revenue growth indicates that an analytical, scientific knowledge base has a positive effect on value creation. In line with Sturman (2003), increasing experience from a low level increases, albeit modestly, revenue growth up to a certain point, but the effect is increasingly negative for a higher level of experience (Figure 5). In response to this finding, enterprises should strike a good balance concerning their employees' experience level. Diversity in education level has a positive effect on revenue growth, while diversity in experience has an opposite negative effect. In line with previous research (Roberson et al., 2017), the contrasting findings indicate that diversity is a multifaceted concept showing different performance effects. We have no clear understanding of why diversity in education level has a positive effect, and diversity in experience has a negative effect, but a plausible explanation is that diversity in education enables comparing different skills and combining different network perspectives, while diversity in experience precludes such attempts. We encourage future research to gain further knowledge about these issues. Finally, innovation has a positive effect on revenue growth. The finding is not surprising as numerous studies have shown positive effects of enterprises pursuing efforts to develop novel or improved products and services (Aarstad et al., 2019). Table 1 summarizes the empirical findings.

5.2 | Theoretical and practical implications

The study contributes to the knowledge of enterprises' dynamic capabilities as it researches a unique natural experiment and analyzes data from multiple data sources. The conceptual model (Figure 1), emphasizing how enterprise-level issues may alleviate the negative consequences of an external shock, addresses the core idea of dynamic capabilities. However, previous research has not taken a similar approach, and in its novelty, we address a viable path for future theoretical and empirical research on dynamic capabilities.

Concerning practical implications, the study shows that some enterprise-level characteristics alleviate revenue losses when faced with an unexpected external shock, while others do not. It moreover shows that some enterprise-level characteristics have positive or negative effects on revenue growth, independent of being exposed to an external shock or not. Altogether, the study shows which enterprise-level characteristics are positive or negative for revenue growth in the presence or absence of an unexpected external shock.

5.3 | Limitations and future research

We acknowledge that enterprises may be exposed to different types of external shocks and where different types of enterprise-level candidates as dynamic capabilities may play different roles. Future research should accordingly aim to study different external shocks, for example, technological or demographic changes. As a dependent variable, we compare the change in enterprises' operating revenues before and after the decline. However, we acknowledge that future research should aim to assess other performance measures such as, for instance, change in operating profits or innovation performance.

Our focus has been to study dynamic capabilities at an enterprise level. However, the higher-level concept of regional resilience, "the capacity to recover from external shocks" (Christopherson et al., 2010, p. 5), should also be similarly addressed in future research. For instance, finding that unrelated education diversity at an enterprise-level alleviated revenue losses when strongly exposed to the external shock may indicate that the concept has a similar effect at a regional level. Moreover, we cannot rule out that unrelated education diversity at a regional level may mediate the effect at an enterprise level. As such, future research should examine this and other potential higher-level carriers of regional resilience when enterprises face an external shock.

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DATA AVAILABILITY STATEMENT

Research data are not shared due to third party restrictions.

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