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Working Paper

Business cycles and start-ups across industries: An empirical analysis for Germany

Jena Economic Research Papers, No. 2017-013

Provided in Cooperation with:

Friedrich Schiller University Jena, Faculty of Economics and Business Administration

Suggested Citation: Fritsch, Michael; Konon, Alexander; Kritikos, Alexander (2017) : Business cycles and start-ups across industries: An empirical analysis for Germany, Jena Economic Research Papers, No. 2017-013, Friedrich Schiller University Jena, Jena

This Version is available at:

<https://hdl.handle.net/10419/174373>

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JENA ECONOMIC RESEARCH PAPERS



2017 – 013

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www.jenecon.de

ISSN 1864-7057

The JENA ECONOMIC RESEARCH PAPERS is a joint publication of the Friedrich Schiller University Jena, Germany. For editorial correspondence please contact markus.pasche@uni-jena.de.

Impressum:

Friedrich Schiller University Jena
Carl-Zeiss-Str. 3
D-07743 Jena
www.uni-jena.de

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Business Cycles and Start-ups across Industries: an Empirical Analysis for Germany¹

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This version: August 25, 2017

Abstract

We analyze whether start-up rates in different industries systematically change with business cycle variables. We mostly find correlations that are consistent with counter-cyclical influences of the business cycle on entries in both innovative and non-innovative industries. Entries into the large-scale industries, including the innovative part of the manufacturing sector, are more strongly influenced by changes in the cyclical component of unemployment, while entries into small-scale industries, like the knowledge intensive services, are merely influenced by changes in the cyclical component of GDP. Business formation may therefore have a stabilizing effect on the economy.

JEL classification: L26, E32, L16, R11

Keywords: New business formation, Entrepreneurship, business cycle, manufacturing, services, innovative industries

¹ We are indebted to Sandra Kublina, Katharina Pijnenburg, and Michael Wyrwich for support in preparing the data and to David Audretsch, Werner Bönte, Christian Dreger, Adam Lederer, Helmut Lütkepohl, Dieter Nautz, Simon Parker, Benjamin Schäfer, and Roy Thurik for comments that helped us improve this paper.

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1 Introduction

Research postulates that macroeconomic factors, such as the business cycle and unemployment levels, influence the number of business entries (Parker 2012a; Köllinger and Thurik 2012). Theoretical considerations suggest that these two variables may unfold either pro- or counter-cyclical effects (see *inter alia* Bernanke and Gertler 1989, Hopenhayn 1992, Francois and Lloyd-Ellis 2003), thus making the relationship between the macroeconomic variables and entrepreneurial entry ambiguous. The direction of the effect is, however, of crucial importance. Pro-cyclical effects may amplify positive and negative economic shocks that may overheat the economy during boom periods and slow down recovery during recessions. Counter-cyclical effects would be beneficial for the economy when the opening of more businesses would spur economic recovery in recessions, while a decline of business entries in boom periods would not further enhance growth.

Empirical analyses of how these two macroeconomic factors influence business entries, report mixed results (Parker 2012a; Sanchis et al. 2015). This holds for longer time periods,⁵ as well as for recent shocks like the great recession after the financial crisis of 2008.⁶ However, it is not just the direction of the effects that is unknown, but also the composition of new businesses started during these periods. In what way do the different stages of the cycle affect innovative start-ups with potential for growth and affect marginal businesses with little or no impact on the economy? In this context, Barlevy (2007) claims that radical innovation positively affects further new businesses to be ventured during boom periods, while Ghatak, et al. (2007), Roman, et al. (2013), and Köllinger and Thurik (2012) argue that recessions may especially stimulate the formation of marginal businesses because of falling wages and lower opportunity costs of entrepreneurial activity. Could it be that even in countries where counter-cyclical relations between the cycle and business entries are observed that innovative businesses with growth potential are more likely to be started during boom periods? The answer to this question is crucial in order to assess whether new business formation has a stabilizing or a de-stabilizing effect over the cycle.

⁵ Grant (1996) or Lee and Mukoyama (2015) find pro-cyclical effects for the US, while Georgellis and Wall (2000) report counter-cyclical effects for the UK. Fritsch, Kritikos and Pijnenburg (2015) also find counter-cyclical effects for Germany.

⁶ Siemer (2014) finds pro-cyclical effects for the US, while Hundt and Sternberg (2014a) find counter-cyclical effects for Germany.

Therefore, this paper investigates how much of the observed variations of the start-up rates in different industries can be attributed to changes in GDP growth and to the unemployment level. Using the start-up information of the ZEW Enterprise Panel we distinguish between innovative and non-innovative industries, as well as between large and small scale industries. We perform the analysis at the NUTS 2 region level so that we are able to control for regional differences with regard to a number of further factors that may influence entrepreneurial entry, in particular, knowledge spillovers and employment in small businesses.

We mostly find correlations that are consistent with counter-cyclical effects on both innovative and non-innovative industries. Entries into large-scale industries including the innovative part of the manufacturing sector increase when unemployment is high and *vice versa*, while there is a significantly negative relationship between changes of GDP and entries into small-scaled businesses, including the knowledge intensive services. Exceptions from this general pattern are the “energy and mining” and the “credit and insurance” sectors. Results remain robust when analyzing several sources of a potential bias.

In the following, Section 2 summarizes the current state of research on how business cycles relate to new business formation and presents the research questions. We then introduce the data in Section 3. Section 4 presents our empirical approaches and describes the results of the analysis. Section 5, concludes.

2 Start-ups over the business cycle: theoretical and empirical research

There is considerable variation in the level of new business formation across industries (Audretsch 1995; Falck 2007). Such difference can be attributed to several factors, including an industry-specific minimum efficient size, qualification requirements, the expected development of demand, and the availability of industry-specific inputs (see Parker 2012a, for an overview). Due to these differences, the effect of the business cycle may considerably vary across industries.

This section reviews previous theoretical and empirical literature on how cyclical changes of GDP (Section 2.1) and unemployment (Section 2.2) relate to the entry of new businesses and derives our main research questions (Section 2.3). For clarifi-

cation, we will label the effect of GDP to be pro-cyclical if the number of entries increases when GDP growth is high; the effect of unemployment is said to be pro-cyclical if the number of new businesses increases when unemployment is low. If the number of entries increases when GDP growth is low or unemployment is high we speak of a counter-cyclical effect. The effect is called a-cyclical if no statistically significant relationship between the business cycle variables and new business formation is found.

2.1 Effects of changes in GDP on start-ups

Various theories were developed to understand how start-ups, including innovative start-ups, react to changes in business cycles (for an overview, see Parker 2012b). Caballero and Hammour (1994) propose a ‘Schumpeterian model’ of creative destruction where new businesses entering the market are more productive than old businesses, such that firm entry drives less productive incumbents out of the market. Given that in their model total current demand drives entry and exit, they show that we should expect increasing entry rates during economic upswings while there should be relatively low levels of new business formation during recessions. Thus, their model proposes a pro-cyclical relationship between variations in GDP and business entries.⁷ In a similar direction, Clementi and Palazzo (2016) argue that in response to boom periods where firms usually realize higher profits, more entrepreneurs may feel attracted to enter markets.

This pro-cyclical effect of GDP changes on start-ups may, however, be limited if we also consider supply side effects. Also the development of resource prices is usually related with changes in GDP development. Production costs, rents, wages and other relevant costs for business entries are typically lower in recessions while boom periods have higher costs (Lewis 2009). Hence, low entry costs might make investments into new businesses more attractive during recessions pointing to a counter-cyclical effect on entry.

⁷ As Caballero and Hammour (1994) focus on the relative number of entries in relation to business closures, they also clarify that in case of increasing business entries during recessions these increasing entry rates need to be overcompensated by even higher numbers of business exits given the reduced overall demand in such times.

Francois and Lloyd-Ellis (2003) and Barlevy (2007) present models where firms are explicitly considered to invest into invention activities. In both models demand expectations play a central role, but the two models differ in one crucial aspect, namely in the timing when firms turn their inventions into innovations. While Francois and Lloyd-Ellis (2003) propose that more firms start to commercialize their ideas during recessions, thus leading to a counter-cyclical influence of business cycles on entrepreneurial entries, Barlevy (2007) makes a case for the opposite, namely that more innovation takes place during boom periods leading to a pro-cyclical effect.

Francois and Lloyd-Ellis (2003) argue in their model that since resource costs are lower during recessions, entrepreneurs starting firms sensitive to such entry costs might prefer to launch their businesses during recessions even if they made their invention in a boom period. Barlevy (2007) explains that firms make more investments into inventions during boom periods and then would not risk any delay, even if such a delay would be efficient from a cost point of view. He argues that entrepreneurs at the cost of inefficiency will not risk that potential competitors might “take their ideas away”, i.e. commercializing the same idea at a higher speed. Thus, the main reasons for the contradicting expectations of the two models are timing and opportunity costs.

Koellinger and Thurik (2012) raise a different reason why there may be more start-ups in recessions that might be particularly relevant for innovative new businesses. By applying the prospect theory to start-up decisions, they argue that “innovative business ideas that entail high risk are more likely to be pursued by individuals who suddenly have lower opportunity costs of self-employment than before, for example, as result of a salary cut or of unemployment in a recession” (Koellinger and Thurik 2012, 1153). This is because in such situations of a loss position in relation to the prospect theory’s reference point, individuals might be more willing to take risk and act less uncertainty averse. According to this argument there should be more innovative start-ups during recessions.

Empirical evidence is inconclusive. Lee and Mukoyama (2015), who restrict their analysis to manufacturing plants, and Clementi and Palazzo (2016), who analyze the overall entry rates for the US, report pro-cyclical effects of output growth. In turn, Glaeser et al. (2010) shows that more entrepreneurs enter the market when fixed costs are lower, which usually holds for recessions. Fritsch, Kritikos and Pijnenburg (2015) who analyze the overall entry rates for Germany find that, new business

formation is higher during recessions than during boom periods. Diverging observations can also be found for the great recession in the aftermath of the financial crisis of 2008. Siemer (2014, 1) observes an “unprecedented decline in firm entry” in the US, while Hundt and Sternberg (2014a, 740) conclude that, “the crisis had the effect of supporting entrepreneurial activities in Germany in general.” Hence, changes in GDP or output levels can have both pro-cyclical and counter-cyclical effects on business entries (see Hundt and Sternberg 2014b). Even more so, it remains unclear which effect prevails in what type of industry.

2.2 Effects of variations in unemployment on start-ups

The second business cycle variable, the level of unemployment, may unfold effects that are different from those of the development of GDP or output. When unemployment is high, it seems plausible to assume that more individuals will set up a business out of unemployment (Caliendo and Kritikos 2010). However, these kind of new businesses may favor industries where starting a firm requires relatively few resources and where the minimum efficient size is comparatively low, such as in small-scale services (Roman et al. 2013). Consequently, high levels of unemployment may particularly induce entries by the extensive margin (the number of firms). During times of low unemployment, entry into such industries can be expected to be lower because it is easier to find a job in dependent employment.

In contrast, the prosperity pull hypothesis argues that during times of low unemployment, newly ventured businesses face higher consumer and firm demand for their products and services as more people have jobs, thus increasing their potential profits, and *vice versa*. If that influence should prevail, fewer businesses would be expected to be opened during times of high unemployment and there should be more start-ups when unemployment is low (Parker 2012a).

Both the unemployment-push and the prosperity pull hypothesis do, however, not account for a further important issue, the availability of resources that may be particularly relevant for firm formation at the intensive margin, i.e. when entrepreneurs aim to establish larger businesses with significant numbers of dependent employees. One may argue that such more ambitious start-ups find more favorable conditions during periods of high unemployment not primarily because the business founders themselves are unemployed, but because high unemployment improves the

availability of labor at relatively low wages. This may be particularly relevant for the venturing of innovative businesses with demand for labor (Francois and Lloyd-Ellis 2003). Thus, high unemployment may also have a positive effect on the number of entries into industries where business founders aim to create innovative and large-scale businesses.

Examining the empirical evidence, Robson (1998) finds no support for a recession push effect for Great Britain, while Georgellis and Wall (2000) in their analysis for Great Britain report a positive relationship between a rising level of unemployment and entrepreneurial entry. Foti and Vivarelli (1994) for Italy, Fairlie (2013) for the US, and Fritsch, Kritikos and Pijnenburg (2015) for Germany, arrive at similar results.⁸ Hence, the overall picture regarding the effect of unemployment on new business formation is more conclusive, as nearly all studies point to a countercyclical influence, i.e. more businesses are opened when unemployment is high, while we are not aware of any evidence supporting the prosperity-pull hypothesis.

This brief outline of the possible relationships between cyclical variations in macro-economic variables and new business formation shows that it is far from clear how these factors, in particular changes in GDP, influence start-up behavior. Since the different effects may only apply to certain types of entry, it is important to distinguish between such types in terms of industries, potential firm sizes, and innovativeness. During times of recessions and of economic prosperity, the entry costs, costs of resources as well as opportunity cost, on the one hand, and current profits and expectations about future profits on the other, can be assumed to unfold differing effects on different industries.

2.3 Industry-specific effects of macroeconomic variables: research questions

Our central concern is how cyclical variables of GDP and unemployment may relate to new business formation conditional on different kinds and sizes of businesses. To distinguish between different kinds of business entries, we follow Holmes and Schmitz (1990) in assuming that individuals with low skills will start firms that have a low potential for innovation, while individuals with high skills will start firms that have

⁸ There is more empirical evidence for other countries, see Parker (2012a) or Fritsch, Kritikos and Pijnenburg (2015).

a higher potential to introduce innovations. In addition to considering two different types of entrepreneurs with different potentials for innovation, we also assume that businesses can be of two different sizes. Many businesses will require no or only a small number of employees, so that they are basically run by the entrepreneurs themselves. Other businesses may, however, demand a larger number of paid employees. Thus, overall we consider four types of entrepreneurs and their businesses that combine innovation potentials and scale:

Type 1 entrepreneurs are low skilled and have a low potential for innovation, while they expect to employ no or only a small number of workers. Examples include trade or consumer services.

Type 2 entrepreneurs may also have a low potential for innovation, but they attempt to create large-scale businesses. Businesses of this type include, for instance, start-ups in non-innovative manufacturing industry.

Type 3 entrepreneurs are highly skilled and have a potential to introduce innovations but their business is expected to be small-scale, e.g. firms in knowledge intensive services.

Type 4 consists of highly skilled entrepreneurs with an innovation potential running large-scale businesses, for example innovative manufacturing.

Given these four different types we may speculate about type-specific effects. Our review of previous research (Section 2.1) showed that variations in the GDP-level can on the one hand unfold demand side effects (i.e. current or future profit opportunities), and on the other hand have supply side effects (i.e. changes of entry cost, early stage production cost, as well as resource cost for labor and capital). Which of these effects prevails is an empirical question. We expect that the more innovative a start-up is, the less current demand and the more demand expectations do play a role. Moreover, the larger the expected size of a newly ventured business, the less will the entrepreneur's opportunity costs matter and the larger the role of other cost categories. Thus, correlations between GDP and business entries will differ by size and innovativeness of the firms.

As to the second business cycle variable, unemployment, we expect that variations in the unemployment rate may influence potential entrepreneurs in different

ways depending on their skill level and the planned size of their business. For individuals with low skills, an increase in unemployment makes it more difficult to find a job, such that avoiding unemployment leads to a stronger incentive to start an own business. Individuals with high skills, who may also have a higher potential for introducing innovations, can be assumed to be less influenced by changes in the general level of unemployment as they may move more easily between alternative job opportunities. For this type, there are less incentives of venturing a business in order to avoid unemployment. Entrepreneurs who plan to venture businesses with a larger number of employees may be more likely to start their ventures in times of high unemployment. Given that there is no evidence of a prosperity-pull effect of a low level of unemployment, the unemployment rate can be expected to generate counter-cyclical effects.

Based on these considerations, we investigate the following three questions:

- (1) To what extent are there differences in the influence of cyclical variables on new business formation, when distinguishing between (a) large and small-scale industries and (b) innovative and non-innovative industries?
- (2) Cyclical variations in GDP: (a) Are demand side effects such as expectations about current or future profit opportunities more or less important for new business formation than supply side effects (e.g., opportunity costs, production and resource costs, other entry-related costs), leading to pro-, a-, or counter-cyclical influences of GDP on business entry? (b) To what extent does the innovativeness and the expected size of a ventured business matter in the cyclical relationship between changes in GDP and business entries?
- (3) Cyclical variations in unemployment: (a) To what extent do changes in the unemployment level unfold counter-cyclical influences on entries of firms with a low innovation potential that do not expect to employ a large number of personnel (Type 1)? (b) To what extent do changes in the unemployment level unfold any influence on entries of firms with a high innovation potential that do not intend to employ a large amount of personnel, but where the entrepreneurs themselves are less affected by unemployment risks (Type 3)? (c) To what extent do changes in the unemployment level unfold counter-cyclical influences on entries of firms that expect to employ a larger number of employees (Type 2 and 4) at times of high unemployment when labor is more easily available?

3 Data and classification of industries

3.1 Data

For our analysis, we use data on start-ups from the Enterprise Panel of the Center for European Economic Research (*ZEW-Mannheim*). This source includes nearly all firms established between 1995 and 2013. The data are based on information from *Creditreform*, Germany's largest credit rating agency, and allow for identifying innovative start-ups based on their affiliation with certain industries. Like other data sources on start-ups, these data may not have complete coverage of solo-entrepreneurs. However, once the firm either is registered, hires employees, asks for a bank loan, or unfolds reasonable economic activities even as a solo entrepreneur, it is included in the data set and information is gathered on the date when the firm was established. Most, solo-entrepreneurs are captured along with the business founding date (for details see Bersch et al. 2014).

In our analysis, we distinguish between a number of sectors and industries covering all parts of the private economy in Germany, except for agriculture.⁹ We differentiate between industries according to their innovativeness and knowledge intensity. Within the manufacturing sector, we apply the common classification of industries according to their presumed innovativeness. In our first group, we include *high-technology manufacturing industries* spending more than 8.5 percent of their annual turnover on Research and Development (R&D), as well as *technologically advanced manufacturing industries* with R&D intensities between 3.5 and 8.5 percent (OECD 2005; Gehrke et al. 2010). These two types of industries are separated from the *non-technology oriented manufacturing industries* that spend less on R&D, as well as from the sectors of *construction*, and *energy and mining*.

Since the service sector is heterogeneous, we distinguish between a number of different sub-sectors, starting with the traditional services such as *trade, transport and postal services*. The *business oriented services* comprise the "other" business services and the knowledge intensive services, which again consist of *technology oriented services* (architectural and engineering activities, technical consultancy, and technical testing and analysis), as well as other *non-technology oriented services*.

⁹ Agriculture is excluded because new business formation in this sector represents a rather special case that is hardly comparable to other sectors.

We have as further categories *credit and insurance* (separately from the business services) and the *consumer oriented services* comprising hospitality, real estate services, health care, culture, sports and entertainment, social services, and education.

As the cyclical developments of GDP and unemployment may differ between regions, the analysis is performed at the level of NUTS 2 regions. Moreover, performing the analysis for regions enables us to account for regional variation of other determinants of new business formation such as knowledge and the share of small business employment. The NUTS 2 level is chosen as it is the most spatially disaggregated level for which the sample size of the data on knowledge-intensive business formation is sufficiently large. Moreover, data on GDP at a spatially more disaggregated level, such as planning regions or NUTS 3, are considerably less reliable. Thus, the number of regions in this analysis is 38.

Many investigations of the relationship between entrepreneurship and the business cycle use changes in the stock of entrepreneurs as the dependent variable (net entry). In contrast, our analysis is based on transitions into self-employment (gross entry). Gross entry is better suited to identify how macro-variables influence entrepreneurship at the industry level as this variable provides information about the dynamics of the economy (see Caballero and Hammour 1994; Nickell 1996). Net entry conceals changes in the gross flows (for an extended discussion, see Fritsch, et al. 2015). Hence, we expect to reveal the relevant relationships more reliably than an analysis based on net entry.

The information on the number of unemployed persons and unemployment rates are provided by the Federal Employment Agency (*Bundesagentur für Arbeit*). The unemployment rate is defined as the share of registered unemployed over the entire working population that comprises all employed plus the registered unemployed. The nominal GDP at the NUTS 2 level is annually provided by *Volkswirtschaftliche Gesamtrechnung der Länder* (Macroeconomic Accounting of the Federal States; Statistisches Bundesamt a, various volumes) for the period 1994-2012. In order to obtain real values of GDP, the nominal figures are deflated by using the annual Consumer Price Index (CPI) of the Federal Statistical Office (Statistische Bundesamt b, various volumes). Since information on the CPI is only available for Federal States, but not for NUTS 2 regions, we deflate the nominal GDP at the NUTS 2 level by using the regional CPI of the corresponding Federal State.

The cyclical component of the unemployment rate and of real GDP is generated applying the Hodrick-Prescott filter (Hodrick and Prescott 1997). This filter is a statistical tool widely used in empirical analyses for separating the cyclical component of economic development from the corresponding trend (Montoya and de Haan 2008). The two components are estimated in a way that, over long periods, the sum of the deviations of the cyclical component from the trend is close to zero, thereby minimizing the variability of the growth component. The so-called smoothing or HP filter parameter determines the variability of the growth component. The larger the HP filter parameter, the smoother the trend component is. Following Ravn and Uhlig (2002), we use a HP filter parameter of 6.25 for annual data.¹⁰

When focusing on start-ups of innovative businesses requiring significant investments into R&D, as well as those needing highly skilled employees, it is important to control for other macroeconomic factors; in particular, those related to knowledge spillovers that also influence entries in such industries. In our approach, we consider four factors that are consistent with the Knowledge Spillover Theory of Entrepreneurship (see Audretsch et al. 2006; Acs et al. 2009) for each NUTS 2 region. These factors are the share of employees in small businesses, the share of workforce with a tertiary degree, the number of university professors, and the number of patents as a proxy for R&D output.

Previous research shows that employees who have worked in small firms have a higher propensity to start an own business (Almeida and Kogut 1999; Elfenbein et al. 2010; Parker 2009) and that the venturing of new businesses is higher in regions where the number of individuals holding a tertiary degree is high.¹¹ We account for both variables by using information on the regional employment share in establishments with up to 20 employees and the share of highly qualified employees, both coming from the Establishment History File of the German Employment Statistics, which covers all employees subject to compulsory social insurance contributions

¹⁰ Using other plausible values of the HP filter parameter does not lead to any fundamental changes of the results. We also discuss the use of a different filter in Section 4.3.3 The deviation from the trend of GDP is computed on the basis of 18 observations per region, whereas to filter unemployment shares we have 17–19 observations per region.

¹¹ According to the Knowledge Spillover Theory of Entrepreneurship, such knowledge should be conducive to start-ups, particularly in innovative and knowledge-intensive industries (Acs, et al. 2009). Fritsch and Aamoucke (2013, 2017) find that such effects of regional knowledge on new business formation in innovative and knowledge-intensive industries are highly localized and hardly spill over to adjacent regions.

(Spengler 2008). It is also known that the proximity to universities matters, as start-ups seek to exploit the regional knowledge stock for spillovers from these institutions (Audretsch et al. 2006; Fritsch and Aamoucke 2013, 2017). We approximate for the knowledge stock by providing information on the number of professors per 1,000 workforce population (see German Federal Statistical Office – *Hochschulstatistik des Statistischen Bundesamts*).¹²

Finally, a higher level of research output may also induce higher start-up rates (see Shane 2001). To account for this influence, we include the yearly number of patent applications per 1,000 workforce population as a measure of a region's knowledge capital; this is provided by the RegStat database. The low correlation between the number of professors and the number of patents (see Table A6 in the Appendix) suggests that the two variables represent distinct types of knowledge that show considerable divergence in their importance across industries. Since a Breitung (2000) panel unit root test reveals that the levels of these independent variables are not stationary, they are included as growth rates. Given restrictions due to data availability and necessary transformations of independent variables¹³ (like the computation of growth rates), our time dimension covers 13 years, from 1996 to 2008.

3.2 Classification of industries

In our conceptual analysis and the resulting research questions (Section 2.3), we distinguish between four types of start-ups according to the innovativeness and the potential size of their ventures. To answer these research questions with data for industries, we need to assign these types of entrepreneurs to different industries. Table 1 presents such a classification of industries that is based on average values of innovativeness and minimum efficient size of the industries. According to the classification, the typical entries of Type 1 are in consumer oriented services, construction, and trade. The entries of Type 2 are in non-innovative large-scale industries such as non-innovative manufacturing, transport, but also energy and mining. Examples for innovative industries with low minimum efficient size, Type 3, are knowledge intensive

¹² The analyses of the role of public research institutions for innovative start-ups in Germany by Fritsch and Aamoucke (2017) show that the number of professors can be regarded a good representation of the respective knowledge stock.

¹³ The independent variables enter the estimation with a time lag of one year.

and technology oriented services as well as credit and insurance. Finally, innovative businesses at a larger scale, Type 4, are the high-tech and technologically advanced manufacturing industries. This classification can of course not fully account for all heterogeneity of start-ups within industries. However, we argue that our analysis is sufficiently valid for an empirical test of our research questions.

Table 1: Classification of industries according to innovativeness and minimum efficient size (scale)

Innovation / scale	Small scale	Large scale
Non-innovative	Type 1: Consumer oriented services, construction, trade	Type 2: Energy and mining, non-innovative manufacturing, transport and postal services
Innovative	Type 3: Credit and insurance, knowledge intensive and technology oriented services	Type 4: High-tech and technologically advanced manufacturing

A debatable case in this classification of industries, according to their minimum efficient size, is energy and mining. This sector traditionally consists of large-scale power plants and includes comprehensive infrastructures for energy distribution that make entry rather difficult. However, it also comprises a growing share of firms that produce energy based on wind, solar power and water on a relatively small scale. Entries of such small-scale energy producers played a considerable role during our period of analysis. This sector may also represent a rather special case because it was subject to a high level of state intervention such as changes in the regulatory framework and subsidization of energy production from renewable resources.

3.3 Descriptive statistics

Table 2 reports descriptive statistics of the start-up rates in different sectors. In the entire private sector (except agriculture), there are an average of 44 start-ups per 10,000 workforce per year. The largest numbers of new businesses are in consumer-oriented services, trade and business oriented services. Relatively low rates are found in manufacturing and in energy and mining. The start-up rates in high-tech manufacturing and technologically advanced manufacturing industries are lower than those in non-innovative manufacturing. In contrast, the number of new businesses in knowledge intensive services is higher (5.6 start-ups per 10,000 workforce).

Table 2: Descriptive statistics for start-up rates in different sectors

Start-up rate for	Mean	Minimum	Maximum	Standard deviation
All private sectors	44.14	30.02	52.19	6.03
- Energy and mining	0.52	0.28	1.02	0.24
- Construction	5.34	3.30	7.40	1.17
- Trade	10.53	6.19	13.36	2.28
- Transport and postal services	1.84	1.17	2.24	0.27
- Credit and insurance	1.67	1.04	2.06	0.31
- Consumer oriented services	12.55	9.04	13.97	1.22
- Manufacturing	2.13	1.58	2.71	0.29
- Non-innovative manufacturing	1.73	1.30	2.13	0.22
- Innovative manufacturing	0.40	0.27	0.58	0.09
• High-tech manufacturing	0.11	0.07	0.16	0.06
• Technologically advanced manufacturing	0.29	0.19	0.41	0.06
- Business oriented services	9.57	7.21	11.41	1.08
- Knowledge intensive services	5.61	3.78	7.08	0.86
• Technology oriented services	2.79	1.95	3.69	0.48

Notes: Yearly number of start-ups per 10,000 workforce in Germany 1995-2013.

Overall, the summary statistics show considerable differences in the magnitude and the variation of business dynamics across sectors. Together with the fact that there may be differences in the economic significance of start-ups across sectors, our observations indicate that an analysis of the influence of the business cycle on start-ups should distinguish between sectors. For instance, a high number of entries into consumer-oriented services may overcompensate for considerably smaller numbers of entries in the manufacturing sector or the technology-oriented services but these fewer start-ups may have stronger effects on future developments.

Examining entries over time, Figure 1 shows declining start-up rates in most economic sectors. This decline is stronger for Type 1, which is mostly driven by the trade sector, partly explaining the high coefficient of variation in this sector (Table 2), but the start-up rates in the innovative industries also show a negative trend over the observation period (see Types 3 and 4 in Figure 1).

The high correlation values of start-up rates within certain sectors reported in Tables A1 and A2 in the Appendix indicate correspondence between new business formations in different fields of economic activity. This is particularly true for start-ups

in the different parts of the service sector suggesting that these start-ups are triggered by similar factors.

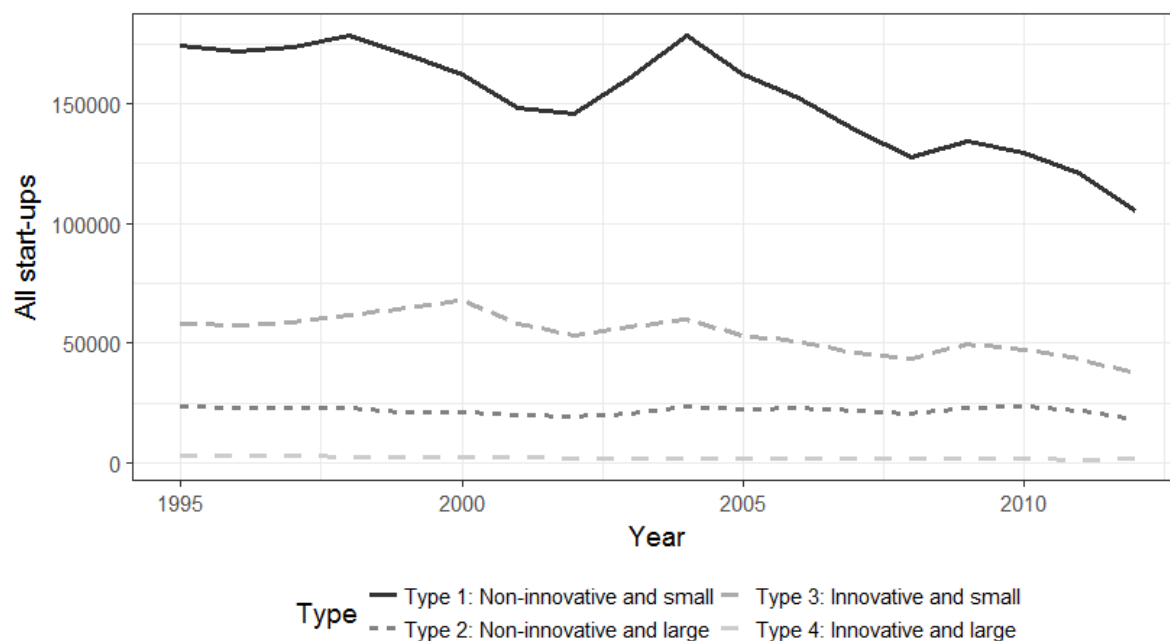


Figure 1: Start-ups conditional on type

The relationship of new business formation in manufacturing with the start-up activity in the service sector is less pronounced, while the correlation of new business formations within the innovative parts of manufacturing are high (Tables A1 and A2 in the Appendix). An exception is the negative correlation of the start-up rates in energy and mining with the level of new business formation in other sectors (Table A1).

Table 3 reports the correlation between start-up rates in different sectors with the cyclical components of the unemployment rate and of GDP. Correlation is strongest for the cycle indicator that is lagged by one year ($t - 1$). While the relationship with the unemployment rate is nearly always positive, it tends to be negative for the cyclical component of GDP, particularly in years t and $t - 1$. The trade sector correlates most with the cyclical component of the unemployment rate, while correlations seem to be stronger for manufacturing than for services. When it comes to the cyclical component of GDP, the contemporaneous and one year lagged correlation is usually negative, while the two-year lagged correlation is mostly positive, probably due to the sinusoidal wave pattern of this variable over time.

Table 3: Correlation between start-up rates in different sectors and business cycle variables

	Unemployment rate – cyclical component			Real GDP – cyclical component		
	T	$t - 1$	$t - 2$	t	$t - 1$	$t - 2$
All private sectors	0.12	0.17	0.04	-0.08	-0.09	0.06
Energy and mining	0.00	-0.04	-0.09	-0.05	-0.11	-0.03
Manufacturing	0.16	0.19	0.01	-0.16	-0.12	0.10
Non-innovative manufacturing	0.16	0.18	-0.02	-0.18	-0.14	0.08
Construction	0.18	0.17	0.04	-0.05	-0.06	0.03
Trade	0.19	0.25	0.05	-0.09	-0.10	0.08
Transport and postal services	0.06	0.15	0.08	0.00	-0.06	0.02
Credit and insurance	0.02	0.08	0.00	-0.02	-0.06	0.06
Business oriented services	0.00	0.04	0.02	-0.04	-0.03	0.04
Consumer oriented services	0.07	0.11	0.02	-0.06	-0.08	0.04
Innovative manufacturing	0.08	0.13	0.07	-0.05	0.00	0.10
High tech manufacturing	0.05	0.14	0.12	0.00	-0.04	0.02
Technologically advanced manufacturing	0.07	0.09	0.03	-0.08	0.03	0.12
Knowledge intensive services	0.00	0.06	0.03	-0.05	-0.04	0.05
Technology-oriented services	0.00	0.09	0.06	-0.06	-0.06	0.05

These correlations suggest that the influence of the cycle on new business formation differs quite considerably across industries. According to the correlations, it takes, on average, about one year for the business cycle to exert its main influence on the formation of new businesses.

The correlation between the GDP cycle and the unemployment cycle is -0.39 (Table A6 in the Appendix), such that a multicollinearity problem due to a strong correlation between the cyclical components is unlikely.¹⁴ Therefore, we include the cyclical component of the unemployment rate and the GDP in all models. There is considerable variation in the GDP and unemployment cycle across regions, as shown in Figure A1 (in the Appendix) that depicts bi-regional correlations between the two cyclical components.¹⁵ The median bi-regional correlation of the GDP cycle is 0.55 and of the unemployment cycle 0.88. Thus, the GDP cycle is less synchronized across regions than the unemployment cycle.

¹⁴ We also computed variance inflation factors, which did not indicate any serious multicollinearity problems.

¹⁵ The bi-regional correlation is computed as $\text{Cor}(v_{i,t}, v_{j,t})$ where v is the cyclical component (of GDP or unemployment) and i and j are two regions with $i \neq j$.

4 Empirical approaches and results

This section presents our empirical results. We start by analyzing short-term business cycle effects in all industries available in our data set. Next, we construct the four types of businesses discussed in section 2.2 and 3.2 and analyze our research questions. We also provide sensitivity checks, including tests for endogeneity.

4.1 Separate analysis for each industry

We aim to assess whether there is evidence that start-up rates in different industries systematically change with business-cycle variables. Therefore, we regress start-up rates on the cyclical components of the unemployment rate and GDP, as well as on a set of control variables related to business entries. The same set of independent variables is included in all models in order to identify differences between industries. We apply a fixed effects panel approach to capture region-specific influences that are invariant over time. To reduce endogeneity problems, all explanatory variables are included with a time lag of one year (Astebro et al. 2013; Buch et al. 2013). As we are mostly interested in short-term correlations, we concentrate on the cyclical components from the previous year. For robustness checks we examine effects using longer lags. Still, we are aware that the fixed effects estimations do not reflect causal relationships. However, we provide tests for endogeneity in Section 4.3.3, when we test the robustness of our results. To allow for an assessment of the relative influence of the estimated coefficients, all variables are standardized with a mean value of zero and a standard deviation of 1. The estimated equation has the form:

$$\text{Startup rate}_{i,t}^k = \mu_i + \alpha_1 \text{BC unemployment}_{i,t-1} + \alpha_2 \text{BC GDP}_{i,t-1} + \boldsymbol{\eta}^\top \mathbf{x}_{i,t-1} + u_{i,t} \quad (1)$$

The $i = 1, \dots, N$ is the number of NUTS 2 regions; $t = 1, \dots, T$ denotes the years, $k = 1, \dots, 15$ stands for the sector (including aggregates such as all private sectors), μ_i represents the fixed effects and $\mathbf{x}_{i,t}$ is the four-dimensional vector of control variables. The control variables (in \mathbf{x}) are, as shown in Section 3.1, the share of employees in businesses with up to 20 employees, the share of employees with a tertiary degree, the number of university professors and of patent applications per 1,000 workforce.

Table 4 presents the results of our fixed effects estimations for start-up rates in different sectors. We start by analyzing how macroeconomic variables affect all start-ups in the overall private sector (Model I). We find positive correlations between the

cyclical component of unemployment and negative correlations between the cyclical component of GDP and new business formation. Among the control variables related to knowledge spillovers, the number of patent applications has the expected positive sign. Importantly, these results are fully consistent with earlier findings for Germany where two different data sources were used (the micro-census and the business registration statistics which could not distinguish between new businesses in different sectors, see Fritsch, et al. 2015). Thus, correlations are consistent with earlier findings according to which the two variables unfold counter-cyclical influences: business formation is higher when unemployment is high, or when GDP is low.

To investigate whether the correlations between the cyclical macroeconomic variables and business formation differ by the innovativeness of the industries, we estimate separate models for all industries (Table 4). Starting with the cyclical component of the unemployment rate, we observe mostly counter-cyclical correlations: high unemployment levels are positively related to entries into manufacturing, both non-innovative and innovative (Models VII and XV), as well as to entries into construction (Model IV) and into the traditional parts of the service sector, i.e. trade and transport services (Models VI and VIII).

In contrast, high unemployment levels do not correlate with the start-up rates in knowledge intensive services (Model XI) or, against expectations, in consumer-oriented services (Model V). The only pro-cyclical correlation that we observe is for entries into credit and insurance (Model X), high when unemployment rates are low. This is the only result that would be consistent with the prosperity-pull hypothesis.

Turning to the influence of changes in GDP on start-ups, there is a counter-cyclical relationship between the cyclical component of GDP and start-up rates in many innovative and non-innovative sectors. This holds true for all kinds of services, knowledge intensive and technology oriented (Models XI and XII), as well as all traditional services (Models V and VIII), but also the construction sector (Model IV). Quite remarkably, except for high-tech manufacturing (Model XIV), entries in most parts of the manufacturing sector remain uncorrelated to changes in GDP. Only entries into the 'energy and mining' sector (Model IX) —about 1% of all start-ups— are positively correlated with the cyclical component of GDP, pointing to a pro-cyclical influence.

Table 4: Influence of cyclical variables on start-ups in different sectors: detailed results for every industry in data and aggregates

	<i>Mixed types</i>			<i>Non-innovative</i>					
	All Types	Small scale	Large scale	Small scale			Large scale		
	I	II	III	IV	V	VI	VII	VIII	IX
Start-up rates in:	All private sectors	Business oriented services	Manufacturing	Construction	Consumer oriented services	Trade	Non-innovative manufacturing	Transport and postal services	Energy and mining
Unemployment rate – cyclical component $t - 1$	0.05***	-0.02	0.11***	0.06***	0.03	0.09***	0.10***	0.08***	-0.02
GDP – cyclical component $t - 1$	-0.17***	-0.10***	-0.06	-0.15***	-0.10***	-0.20***	-0.04	-0.08***	0.13***
Share of employees in small businesses $t - 1$	0.02	0.04	0.02	0.00	0.02	-0.02	-0.02	-0.01	-0.08***
Share of employees with tertiary education $t - 1$	-0.08**	-0.02	0.02	-0.15***	-0.07**	-0.06	0.04	-0.03	0.04
Number of professors per 1,000 workforce $t - 1$	0.03	0.02	0.06**	0.03	0.01	0.03	0.07**	0.01	-0.02
Number of patent applications per 1,000 workforce $t - 1$	0.09***	0.02**	0.10**	0.10***	0.01	0.20***	0.07	0.04	-0.12**
Constant	-0.27***	0.29***	0.32	-0.41***	-0.60***	-0.42***	0.14***	-0.03***	-0.57***
R ²	0.71	0.82	0.62	0.75	0.79	0.56	0.62	0.87	0.36

Notes: Fixed effects panel estimates. ***, ** statistically significant at the 1 percent and the 5 percent level, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are clustered at the region level.

Table 4 *continued*

	<i>Innovative</i>					
	Small scale			Large scale		
	X	XI	XII	XIII	XIV	XV
Start-up rates in:	Credit and insurance	Knowledge intensive services	Technology oriented services	Technologically advanced manufacturing	High-tech manufacturing	Innovative manufacturing
Unemployment rate – cyclical component $t - 1$	-0.08***	-0.01	0.01	0.07**	0.09***	0.09***
GDP – cyclical component $t - 1$	-0.30***	-0.12***	-0.18***	-0.04	-0.14***	-0.09
Share of employees in small businesses $t - 1$	0.05	0.08***	0.17***	0.09***	0.15***	0.13***
Share of employees with tertiary education $t - 1$	-0.13**	-0.04	-0.06	-0.03	-0.01	-0.02
Number of professors per 1,000 workforce $t - 1$	0.01	-0.03**	0.03	0.04**	0.02	0.03
Number of patent applications per 1,000 workforce $t - 1$	0.05	0.06***	0.10***	0.16***	0.12**	0.16***
Constant	0.00	0.29***	0.62***	0.67***	0.47***	0.68***
R ²	0.40	0.77	0.72	0.32	0.48	0.43

Notes: Fixed effects panel estimates. ***, ** statistically significant at 1 percent and 5 percent, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are clustered at the region level.

When focusing on business entries into the innovative parts of the industries, an important difference occurs: the influence of cyclical deviations from unemployment and from GDP levels differ systematically between the manufacturing and the service sector. Changes in unemployment levels lead to counter-cyclical correlations with the innovative part of the manufacturing sector but not with the innovative part of the service sector. While changes in GDP levels are correlated with business entries into knowledge intensive and technology oriented services (Models XI and XII representing all innovative parts of the service sector), in the manufacturing sector it only

correlates with start-up rates in high-tech manufacturing (Model XIV). Table 5 summarizes all correlations conditional on the type of innovativeness and scale.

Table 5: Effect on business cycle variable on new business formation in different types of industries

Type	Industry	GDP	Unemployment
Non-innovative and small scale	Construction	-	-
	Consumer oriented services	-	0
	Trade	-	-
Non-innovative and large scale	Non-innovative manufacturing	0	-
	Transport and postal services	-	-
	Energy and mining	+	0
Innovative and small scale	Credit and insurance	-	+
	Knowledge intensive services	-	0
	Technology-oriented services	-	0
Innovative and large scale	Technologically advanced manufacturing	0	-
	High-tech manufacturing	-	-

Notes: “+” indicates a pro-cyclical effect, “-” a counter-cyclical effect and “0” no cyclical effect.

At the industry level, the results for the control variables are mostly in accordance with results of previous studies. The share of employees in small businesses has the expected positive sign if statistically significant (except for energy and mining). The variation of the results for the three variables representing distinctive facets of the regional knowledge stock—share of employees with a tertiary degree, number of professors per workforce, and number of patent applications per 1,000 employees— demonstrates differences in the relevant knowledge base for start-ups across industries. Regional knowledge, in particular patents, has a positive influence when focusing on the innovative industries, but also on the non-innovative part of the secondary sector, while it does not seem to play a role for new business formation in the non-innovative service sectors. The findings are consistent with the Knowledge Spillover Theory of Entrepreneurship (Audretsch et al. 2006; Acs, et al. 2009).

4.2 Type-specific analysis

To further analyze our research questions proposed in Section 2.3 we use our data on entries into different industries to construct the four types as proposed in Table 1. Instead of Equation (1), we, now, estimate the following model:

$$\text{Startup rate}_{i,t}^{\tau} = \mu_i^{\tau} + \alpha_1^{\tau} \text{BC unemployment}_{i,t-1} + \alpha_2^{\tau} \text{BC GDP}_{i,t-1} + \boldsymbol{\eta}_{\tau}^{\top} \mathbf{x}_{i,t-1} + u_{i,t}^{\tau} \quad (2)$$

where $\tau \in \{\text{Type 1, Type 2, Type 3, Type 4}\}$ captures the industry type and all other variables in (2) also depend on the type. Table 6 provides results conditional on type. Using Table 6, we obtain the following results with respect to our research questions.

In relation to research question 1, we find that the two cyclical macroeconomic variables influence new business formation in a different way. Hence, the industry context that stands for demand conditions, technologies, production methods, and cost structures matters quite significantly.

In relation to research question 2, we find virtually no correlation that is consistent with a pro-cyclical effects of GDP, as proposed by Rampini (2004), Barlevy (2007) and others. Rather to the contrary, we observe correlations that are consistent with a counter-cyclical influence of GDP on business entries, but only for entries into all small-scale industries (Type 1 and Type 3), while entries into large-scale industries remain mostly uncorrelated to GDP. So, it is the size that matters for the relationship between the cycle and business entries.

Table 6: Influence of cyclical variables on start-ups conditional on the four types

Start-up rates in:	Type 1: non-innovative and small	Type 2: non-innovative and large	Type 3: innovative and small	Type 4: innovative and large
Unemployment rate – cyclical component $t - 1$	0.08**	0.10***	-0.01	0.09***
GDP – cyclical component $t - 1$	-0.19***	-0.03	-0.17***	-0.09
Share of employees in small businesses $t - 1$	0.00	-0.05	0.11***	0.13***
Share of employees with tertiary education $t - 1$	-0.11**	0.01	-0.06**	-0.02
Number of professors per 1,000 workforce $t - 1$	0.03	0.02	0.03	0.03
Number of patent applications per 1,000 workforce $t - 1$	0.13***	0.01	0.07***	0.16***
Constant	-0.62***	-0.21***	0.36***	0.68***
R ²	0.63	0.75	0.73	0.43

Notes: Fixed effects panel estimates. ***, ** statistically significant at the 1 percent and the 5 percent level, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are clustered at the region level.

In relation to research question 3, the correlations between unemployment and business entries point to counter-cyclical influences on entries by Type 1 (the small-scaled non-innovative businesses, question 3a) while its influence is a-cyclical in sectors with a high innovation potential that have small average sizes (Type 3, question 3b). Moreover, correlations between unemployment and business entries also point to counter-cyclical influences on entries into Types 2 and 4, the large-scale industries (question 3c). In summary, there is more of a “size effect”, with changes in GDP being related to business entries into small-scale industries while changes in unemployment relate more strongly to entries into large-scale industries where both relations apply for innovative industries.

4.3 Robustness tests

We performed several sensitivity tests to examine the robustness of our findings.

4.3.1 Effect dynamics

As a first robustness test, we compare the results from the model using one lag (one year) given in equation (2) to a model capturing short-run dynamics of two prior years:

$$\begin{aligned} \text{Startup rate}_{i,t}^{\tau} = & \tilde{\mu}_i^{\tau} + \alpha_{1,1}^{\tau} \text{BC unemployment}_{i,t-1} + \alpha_{1,2}^{\tau} \text{BC unemployment}_{i,t-2} \quad (3) \\ & + \alpha_{2,1}^{\tau} \text{BC GDP}_{i,t-1} + \alpha_{2,2}^{\tau} \text{BC GDP}_{i,t-2} + \boldsymbol{\eta}_{\tau,1}^{\top} \mathbf{x}_{i,t-1} + \boldsymbol{\eta}_{\tau,2}^{\top} \mathbf{x}_{i,t-2} + \tilde{u}_{i,t}^{\tau} \end{aligned}$$

where all variables are included with a lag of two periods. We are interested in the cumulative correlations of unemployment, $\alpha_{1,1}^{\tau} + \alpha_{1,2}^{\tau}$, and the GDP cycle, $\alpha_{2,1}^{\tau} + \alpha_{2,2}^{\tau}$. Results are provided in Table 7. We report results for unemployment and GDP.¹⁶

The results of the analysis with two time lags (Table 7) are consistent with the analysis using only one year (Table 6). The only difference is that there is no correlation between unemployment and start-ups of Type 1 in the distributed lag model, which is because unemployment effects with a lag of one and two periods cancel each other out.

¹⁶ Additional results are provided on request.

Table 7: Short-run dynamics of the influence of cyclical variables on start-ups conditional on the four types

Start-up rates in:	Type 1: non-innovative and small	Type 2: non-innovative and large	Type 3: innovative and small	Type 4: innovative and large
Unemployment rate – cyclical component $t - 1$	0.06**	0.10***	-0.01	0.07**
Unemployment rate – cyclical component $t - 2$	-0.07***	0.08***	-0.04	0.02
GDP – cyclical component $t - 1$	-0.20***	-0.06	-0.17***	-0.07
GDP – cyclical component $t - 2$	0.02	0.01	0.01	0.03
Cumulative effect of unemployment	-0.01	0.18***	-0.05	0.09***
Cumulative effect of GDP	-0.18**	-0.05	-0.16***	-0.04

Notes: Fixed effects panel estimates. ***, ** statistically significant at the 1 percent and the 5 percent level, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by two periods. The number of observations is 418 (38 cross sections, 11 years) in all models. Standard errors are clustered at the region level.

4.3.2 Potential endogeneity bias

Consider the following model for business entry:

$$\text{Entry} = v \text{Business cycle variable} + bY + \epsilon_1 \quad (4)$$

where indices (such as the time index) are dropped for notational convenience. The variable Y includes \mathbf{x} control variables, a constant, region fixed effects, and potentially additional variables. As we are interested in the influence of the business cycle, v is the coefficient of interest. The OLS estimate of v is unbiased if the business cycle variable and the error ϵ_1 are not correlated. Since we include all business cycle variables in lags, the likelihood of such a correlation is small. However, to examine whether results are robust to relaxing the assumption of exogeneity, we perform several instrumental-variable-based checks.

To examine a plausible mechanism generating correlation between the business cycle variable and the error, consider the following model for the business cycle:

$$\text{Business cycle variable} = cY + \epsilon_2 \quad (5)$$

If ϵ_1 and ϵ_2 are correlated, OLS estimates of v will be biased. This might happen if, for instance, there is an unobserved variable U driving business cycle and entry at the same time, i.e. $\epsilon_1 = U + \check{\epsilon}_1$ and $\epsilon_2 = dU + \check{\epsilon}_2$, where $\check{\epsilon}_1$ and $\check{\epsilon}_2$ are idiosyncratic errors.

We try to account for potential endogeneity by applying the instrumental-variable method. In the given setting, we need an instrument for the unemployment and GDP cycle, which enters (5) but not (4).

A reasonable instrument for unemployment is the implementation of one of the so-called *Hartz* labor market reforms at the beginning of the year 2005. Before this reform, non-employed individuals receiving social welfare were not required to be available to the labor market. After the implementation of the reform, individuals received a new form of unemployment benefits (instead of social welfare) and were required to be available to the labor market. While the reform was implemented on January 1, 2005, it generated an incentive for individuals receiving social welfare to register as unemployed already in 2004, as the unemployment benefits were higher than the social welfare payments.¹⁷ As the registering as unemployed required availability to the labor market, the reform resulted in an increase in unemployment without directly affecting start-up incentives in 2004. A fact that might weaken the exclusion restriction is that an earlier part of the reform was a start-up subsidy for entrepreneurship out of unemployment, the so-called “Ich-AG.” However, the subsidy started already two years earlier on January 1, 2003. Furthermore, we tested whether the subsidy might influence results by removing all types of services from small scale businesses, as this is the most common type of start-ups from unemployment (Caliendo and Kritikos 2010), and obtained similar results.¹⁸

An instrument for the GDP cycle is the pre-crisis peak in 2007. As the German economy is highly export-oriented, the German economy was affected by the pre-crisis boom in the US through trade links. As in the pre-crisis period US GDP and, through the trade channel, then German GDP was pushed above the trend by forces not directly related to the German economy, the pre-crisis boom is a candidate for a valid instrument. The financial crisis might have affected start-ups through the finance channel. To control for this channel, in an additional regression we remove the start-ups in the banking industry and include them as a covariate, approximating the health of this sector.

¹⁷ See German newspaper reports from this period (for instance, Rosenfeld 2005 or Spiegel 2005).

¹⁸ Results are available on request.

We estimate separate models for the effects of unemployment and GDP by two-stage least squares. Since the approach removes considerable amounts of variance from the cyclical variables, as the instruments are effectively time dummies, and there is not much variance in case of Type-4 entries (Figure 1), we aggregate the types and consider only effects on small- and large-scale industries. First stages are given in Table A7 (unemployment) and A8 (GDP) in Appendix A. Table 8 shows results of second stage regressions. The instruments have sufficient strength (see the F-test in Table 8). In line with previous results, entry into small-scale industries is mostly counter-cyclically influenced by GDP, whereas entry into large-scale industries is mostly counter-cyclically influenced by unemployment. Table A9 in the Appendix provides results where banking is removed from small-scale industries and entries into banking are included as an additional covariate. Results are consistent with Table 8, although the size of the GDP cycle effect on entries into small-scale industries is smaller.

Models using the two instruments are exactly identified such that instrument validity cannot be tested. However, if certain conditions are met, it is possible to construct additional instruments, to be able to perform a Sargan-Hansen test. Let the structural system be given by (8) and (9). In this case, a recently developed instrumental variable approach proposed by Lewbel (2012) demonstrates that, by exploiting potential heteroskedasticity in the error term in (9), it is possible to consistently estimate effects without an available exclusion restriction if certain assumptions hold. Let Z denote a set of variables that are exogenous and that affect start-ups and the business cycle variable, i.e. they are part of (8) and (9). Z can include some or all elements of Y . In addition to the standard conditions, viz. $\mathbb{E}[Y\epsilon_1] = 0$, $\mathbb{E}[Y\epsilon_2] = 0$, and $\mathbb{E}[YY^T]$ is non-singular, the approach of Lewbel (2012), which we refer to as Lewbel IV, requires that $\text{Cov}(Z, \epsilon_1\epsilon_2) = 0$ and $\text{Cov}(Z, \epsilon_2^2) \neq 0$. If the conditions hold, $(Z - \bar{Z})\epsilon_2$ is a valid instrument for the business cycle variable, where \bar{Z} is the sample average of Z . If $\text{Cov}(Z, \epsilon_2^2) \neq 0$ does not hold, the instrument will be weak (Lewbel 2012) such that testing for instrument strength indirectly tests for the assumption.

Table 8: Influence of the unemployment and GDP cycle on start-ups conditional on size given that the unemployment or GDP cycles are instrumented

Start-up rates in:	Small scale industries		Large scale industries	
Unemployment rate – cyclical component $t - 1$ (instrumented by labor market reform)	-0.01		0.10**	
GDP – cyclical component $t - 1$ (instrumented by pre-crisis boom)		-0.55***		-0.09
Share of employees in small businesses $t - 1$	-0.03	0.14***	-0.05	-0.05**
Share of employees with tertiary education $t - 1$	-0.12	-0.08**	0.00	-0.02
Number of professors per 1,000 workforce $t - 1$	0.02	0.04	0.03	0.03
Number of patent applications per 1,000 workforce $t - 1$	0.17***	0.06**	0.04	0.05
Constant	-0.31***	-0.19***	-0.12	-0.09
F-test for weak IV	23.96	134.38	23.96	134.38

Notes: ***, ** statistically significant at the 1 percent and the 5 percent level, respectively; IV estimation with fixed effects; business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are clustered at the region level.

To construct the instrument, we assume that Z includes the share of employees in small businesses, the share of employees with tertiary education, and the number of patent applications. The selection is based on the criterion of sufficient instrument strength. Using Z constructed in such a way, we tested if the errors in Equation (5) are heteroskedastic, a test if $\text{Cov}(Z, \epsilon_2^2) \neq 0$ holds, could reject homoskedasticity at the 5% level using a Breusch-Pagan test.

Thus, we could not find violations of the Lewbel (2012) conditions for instrument construction. Lewbel (2012) instruments are combined with the instruments we already used for unemployment and GDP and the model, which is now over-identified, is estimated with IV-GMM. Results are presented in Table 9. The F-test results at the first stage (see Table 9) suggest that the generated instruments are not weak. Results show that there is no significant counter-cyclical influence of unemployment on entries into small-scale industries but entries into this type of industries are still counter-cyclically influenced by GDP. In case of large-scale industries, the only statistically significant business cycle effect is a counter-cyclical influence of unemployment. Hence, results are consistent with previous estimation results.

Table 9: Influence of the unemployment and GDP cycle on start-ups conditional on size given that effects are estimated with a combination of Lewbel IV and traditional IV

Start-up rates in:	Small scale industries		Large scale industries	
Unemployment rate – cyclical component $t - 1$ (instrumented by labor market reform and Lewbel instrument)	0.15***		0.26***	
GDP – cyclical component $t - 1$ (instrumented by pre-crisis boom and Lewbel instrument)		-0.54***		0.01
Share of employees in small businesses $t - 1$	0.01	0.14***	0.04	-0.08**
Share of employees with tertiary education $t - 1$	-0.09***	-0.08***	-0.00	-0.02
Number of professors per 1,000 workforce $t - 1$	0.03	0.04	0.03	0.02
Number of patent applications per 1,000 workforce $t - 1$	0.15***	0.05	-0.01	0.07**
Constant	-0.32***	-0.19	-0.32***	-0.11
Sargan-Hansen test (p-value)	0.07	0.74	0.20	0.70
Partial F-test for weak IV	12.40	43.57	12.40	43.57

Notes: ***, ** statistically significant at the 1 percent and the 5 percent level, respectively; IV-GMM estimation with fixed effects; business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are heteroskedasticity robust.

As the system is now over-identified, we can perform a Sargan-Hansen test to examine whether there is indication that the exclusion restriction for the 2004-reform and the 2007-pre-crisis-peak instruments does not hold. The hypothesis that over-identifying restrictions are valid cannot be rejected at the 5% level (Table 9) suggesting that the instruments are valid (conditional on validity of the Lewbel instruments).

4.3.3 Detrending technique

An open concern is that results might be driven by the detrending technique. The Hodrick-Prescott filter has a free parameter, set by the user of the procedure and not driven by data that might influence results (Schlicht 2005). Furthermore, the filter has an end-point bias (Mise, Kim and Newbold 2005). Therefore, to check the robustness of the results, we use an alternative filter, developed by Baxter and King (1999). The Baxter-King filter, isolating the cyclical component from the trend, was explicitly designed to overcome the drawbacks of the Hodrick-Prescott filter.

In line with the recommendations of Baxter and King (1999) for annual data, the minimum period of oscillation is set to 2 and the maximum period to 8, while the

order of the filter is 3. Results are given in Table A10 in the Appendix. Nearly all results under the Baxter-King filter are consistent with those from the Hodrick-Prescott filter. The only exception is the correlation between unemployment and entries by Type 4, which is now a-cyclical, instead of counter-cyclical, when using the Baxter-King filter. This could be a result of the end-point bias of the Hodrick-Prescott filter. However, as results obtained using the Baxter-King filter are numerically similar to results in Table 6 for the remaining three types, it is more likely that the statistical insignificance results from the fact that the Baxter-King filter removes around 80 data points (data at the beginning and end of each time series in each region).

4.3.4 Unobserved spatial links between regions

Studies examining the connection between the business cycle and business entries usually do not account for unobserved spatial links. For instance, Köllinger and Thuri (2012) use a country level panel and control for country fixed effects, but do not control for unobserved dependencies between countries. However, previous studies demonstrate that German municipalities compete on taxes (Büttner 2001), spending (Borck, et al. 2007), and debt (Borck, et al. 2015). This type of competition is unobserved in our model and would enter it through the error term. To test whether our results are sensitive to including unobserved spatial dependencies, we estimate a spatial error model with spatial fixed effects (see Appendix B).

The results of this estimation (Table B1, Appendix B) are consistent with previous results, confirming the counter-cyclicity of both macro-economic variables. The only difference compared to Table 6 is that the correlation between unemployment and Type-1 entries is insignificant after introducing spatial dependencies. Thus, with spatial dependencies, the difference between small and large businesses becomes more pronounced, similar to the result when we investigate effect dynamics with two lags. Entries into small-scale businesses react counter-cyclically to GDP and a-cyclically to unemployment, while entries into large-scale businesses mostly react counter-cyclically to unemployment and a-cyclically to GDP (Table B1 in Appendix B).¹⁹

¹⁹ As further robustness checks we ran the models for low-density and high-density regions as well as for East and West Germany separately. However, we did not find any significant differences between these spatial categories.

5 Summary and conclusions

While nearly all previous empirical analyses of the effect of the business cycle on new business venturing examine start-ups in the overall private sector, our study systematically distinguishes between different industries. We find distinct variations how the variables that represent the business cycle are correlated with new firm formation across industries. Overall, our analysis with data for German NUTS 2 regions indicates correlations that are consistent with mostly counter-cyclical effects of the business cycle on entries into the market, either more businesses are started when unemployment is high or when GDP is low. Moreover, correlations differ more between large- and small-scale industries than between innovative and non-innovative industries in the sense that entries into large-scale industries are mainly influenced by variations in unemployment, while entries into small scale industries—all kinds of services—are affected by variations in GDP. Both results are robust to applying different model specifications.

Overall, in virtually no industry is a GDP level above the trend correlated with increasing entries. Although we are not able to make causal interpretations, this observation points to the conclusion that favorable conditions in terms of high GDP might not be germane for start-ups. In fact, according to our results, it is the other way around: an economic downturn, maybe in the sense of lower production or lower entry costs or better future profit opportunities, seems to be a more favorable environment for innovative businesses than boom periods. This holds at least for entries of small-scale businesses, while entries of large-scale businesses are uncorrelated to changes in GDP. We further interpret our second results—the positive correlations between unemployment and entries of large-scaled businesses—as an indicator that these entries are influenced by easier availability of labor when unemployment is high. Moreover, we should also emphasize that we find no correlation between unemployment and entries into consumer services that make more than 25% of all entries. This industry is commonly assumed to provide a well-suited environment for an unemployment push effect for necessity entrepreneurs. All together, these results are in strong contrast to earlier research (see Ghatak, et al. 2007; Köllinger and Thurik 2012; Roman, et al. 2013) that did not distinguish between entries into different industries but assumed that opportunity driven start-ups should be expected more frequently during boom periods.

Our findings clearly demonstrate the importance of accounting for industry-specific characteristics when analyzing the relationship between the business cycle and new business formation. Since there is little other empirical evidence on industry differences of the effects of the business cycle on new business formation available, more research on this topic is needed. It would be desirable to have similar studies for other countries, particularly for countries like the US where overall pro-cyclical effects seem to prevail. It would be important to understand why in some countries pro-cyclical and in other countries counter-cyclical influences predominate. Is it that in some countries supply-side effects such as production cost influence entry decisions while in other countries it is the demand side? Or do profit expectations during boom periods and recession differ between countries?

Since new businesses, particularly innovative start-ups, may have a positive effect on economic development (Acs et al., 2009, Fritsch 2013; Kritikos 2014), they might play a crucial role in reducing effects of aggregate economic shocks and supporting economic recovery. Hence, it would be important to analyze how cycle-induced entries affect economic development for instance in terms of employment. Empirical analysis for the US points again to opposing results. While Lee and Mukoyama (2015) find for the US manufacturing sector that firms opened during recessions start with about 30% more employees than firms opened during boom periods, Sedláček and Sterk (2017), analyzing entries into all industries, find the opposite, namely more job creation in firms opened during boom periods.

Generally, it would be important to have data that comprise more information about the characteristics of the new businesses in each of these industries, such as their size, the timing and the amount of innovation efforts, as well as the timing of the commercialization of innovative ideas. Such data could allow for a more precise identification of different types of new ventures and, thus, for a more causal interpretation of the results. Moreover, it would be interesting to identify industry-specific cycles and their effects on new business formation. This would particularly allow for comparing the effects of global conditions such as the nationwide levels of unemployment and GDP with industry-specific developments. To these ends, more empirical research on the effect of the business cycle on new business formation is needed.

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Appendix A: data characteristics and robustness

Table A1: Correlation between start-up rates in different sectors

	All private sectors	Energy and mining	Manufac- turing	Construc- tion	Trade	Transport and postal services	Credit and insur- ance	Business oriented services
Energy and mining	-.60	1	-	-	-	-	-	-
Manufacturing	.75	-.34	1	-	-	-	-	-
Construction	.96	-.66	.69	1	-	-	-	-
Trade	.96	-.72	.80	.95	1	-	-	-
Transport and postal services	.95	-.53	.68	.95	.91	1	-	-
Credit and insurance	.90	-.67	.46	.85	.84	.84	1	-
Business oriented services	.88	-.48	.46	.79	.74	.79	.92	1
Consumer oriented services	.95	-.36	.70	.86	.84	.91	.85	.91

Table A2: Correlation between start-up rates in predominantly innovative industries

	All private sectors	Innovative manufacturing	High tech manufacturing	Technologically advanced manufacturing	Non-innovative manufacturing	Knowledge intensive services
Innovative manufacturing	.76	1	-	-	-	-
High tech manufacturing	.78	.98	1	-	-	-
Technologically advanced manufacturing	.74	.99	.96	1	-	-
Non-innovative manufacturing	.68	.72	0.75	0.69	1	-
Knowledge intensive services	.93	.74	.76	.72	0.59	1
Technology-oriented services	.88	.81	.84	.79	0.60	.98

Table A3: Classification of industries

Industry or sector	Industry codes (NACE 1993)
All private sectors	10 – 93 (without 91)
Energy and mining	10, 11, 12, 13, 14, 40, 41
Manufacturing	15 - 37
High-tech manufacturing industries	23.30, 24.20, 24.41, 24.61, 29.11, 29.60, 30.02, 31.62, 32.10, 32.20, 33.20, 33.30, 35.30
Technologically advanced manufacturing industries	22.33, 24.11, 24.12, 24.13, 24.14, 24.17, 24.30, 24.42, 24.62, 24.63, 24.64, 24.66, 29.12, 29.13, 29.14, 29.31, 29.32, 29.40, 29.52, 29.53, 29.54, 29.55, 29.56, 30.01, 31.10, 31.40, 31.50, 32.30, 33.10, 33.40, 34.10, 34.30, 35.40
Non-technology oriented manufacturing	15 – 37 without high tech and technologically advanced manufacturing industries
Construction	45
Trade	50, 51, 52
Transport and postal services	60, 61, 62, 63, 641
Credit and insurance	65, 66, 67
Technology oriented services	642, 72, 731, 742, 743
Non-technology oriented services	73.2, 74.11, 74.12, 74.13, 74.14, 74.4
Knowledge intensive services	Technology and non-technology oriented services
Other business oriented services	71.1, 71.2, 71.3, 74.5, 74.6, 74.7, 74.8 (without 74.87), 90
Business oriented services	Technology oriented, non-technology oriented, and other business oriented services
Consumer oriented services	55, 70 71.4, 80.4, 85, 92, 93

Table A4: Definition of variables

Variable	Definition
Start-up rate	Number of newly founded firms in the industry ^a per 10,000 regional workforce ^b .
Unemployment rate – cyclical component	Number of registered unemployed persons over the entire working population. ^c
GDP – cyclical component	Nominal GDP divided by the annual consumer price index (CPI) of the Federal Statistical Office. ^d
Employees in small businesses	Share of employees in establishments with less than 20 employees. ^b
Employees with tertiary education	Share of employees with a university degree. ^b
Number of professors	Number of university professors at universities in the region in the respective year per per 1,000 workforce. ^e
Patent applications	Number of patent applications with an inventor residing in the region ^e per 1,000 workforce. ^f

Data Sources: a) ZEW Mannheim Enterprise Panel. b) Establishment History File of the Social Insurance Statistics. c) Federal Employment Agency. d) Federal Statistical Office, Working Committee "Volkswirtschaftliche Gesamtrechnung der Länder". e) German University Statistics, Federal Statistical Office. f) RegPat database. g) Deutsche Bundesbank.

Table A5: Descriptive statistics for independent variables

	Mean	Minimum	Maximum	Standard deviation
Unemployment rate – cyclical component (normalized)	-0.363	-2.52e-09	1	0.164
GDP – cyclical component (normalized)	0.607	-1.29e-08	1	0.061
Employees in small businesses	0.307	0.219	0.419	0.044
Employees with tertiary education	0.239	0.139	0.416	0.057
Number of professors	0.431	0.048	1.227	0.208
Patent applications	0.135	0.036	0.353	0.061

Table A6: Correlations among variables

	1	2	3	4	5
1 Unemployment rate – cyclical component	1				
2 GDP – cyclical component	-0.390	1			
3 Employees in small businesses	0.015	0.033	1		
4 Employees with tertiary education	-0.057	-0.026	-0.421	1	
5 Number of professors	-0.003	0.013	-0.398	0.338	1
6 Patent applications	-0.179	0.092	-0.382	0.101	-0.003

Table A7: First stage for unemployment cycle, where unemployment is the dependent variable

2004 labor market reform	0.61***
Share of employees in small businesses $t - 1$	-0.27***
Share of employees with tertiary education $t - 1$	-0.20***
Number of professors per 1,000 workforce $t - 1$	-0.04
Number of patent applications per 1,000 workforce $t - 1$	0.30***
Constant	-0.05

Notes: Fixed effects panel estimates. ***, ** statistically significant at the 1 percent and the 5 percent level, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered variables. Besides the instrument, the remaining independent variables are included in growth rates. All variables besides the instrument are lagged by one period, including the dependent variable. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are clustered at the region level.

Table A8: First stage for GDP cycle, where GDP is the dependent variable

2007 pre-crisis boom	1.29***
Share of employees in small businesses $t - 1$	0.24***
Share of employees with tertiary education $t - 1$	0.04
Number of professors per 1,000 workforce $t - 1$	0.04
Number of patent applications per 1,000 workforce $t - 1$	-0.15***
Constant	0.13***

Notes: Fixed effects panel estimates. ***, ** statistically significant at 1 percent and 5 percent, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered variables. Besides the instrument, the remaining independent variables are included in growth rates. All variables besides the instrument are lagged by one period, including the dependent variable. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are clustered at the region level.

Table A9: Influence of the GDP cycle on start-ups conditional on size given that the GDP cycle is instrumented by the 2007 pre-crisis peak

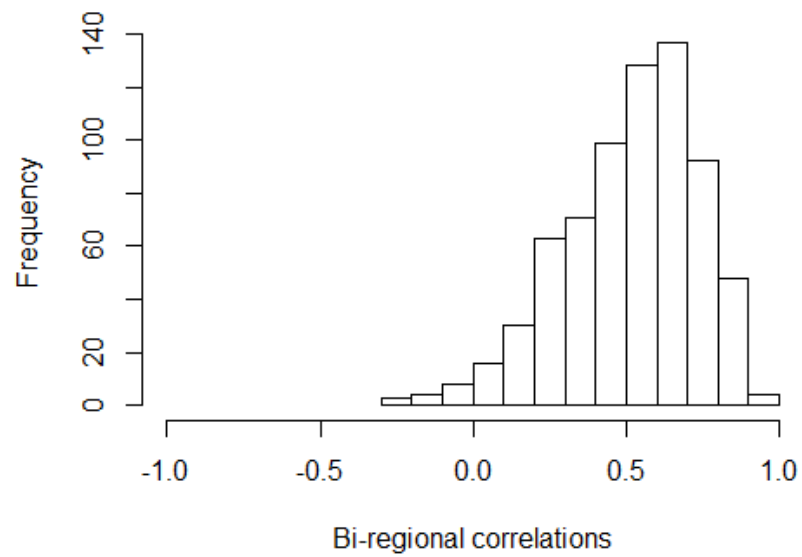
Start-up rates in:	Type 1 + 3 without banking: small size industries	Type 2 + 4: large size industries
GDP – cyclical component $t - 1$ (instrumented by pre-crisis boom)	-0.36***	-0.09
Share of employees in small businesses $t - 1$	0.06**	-0.05
Share of employees with tertiary education $t - 1$	-0.03	-0.01
Number of professors per 1,000 workforce $t - 1$	0.02	0.02
Number of patent applications per 1,000 workforce $t - 1$	0.09***	0.05
Entries into credit and insurance $t - 1$ (proxy for “health” of finance sector)	0.33***	0.04
Constant	-0.22***	-0.09***

Notes: Instrumental variables estimations with fixed effects. ***, ** statistically significant at 1 percent and 5 percent, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 494 (38 cross sections, 13 years) in all models. Standard errors are clustered at the region level.

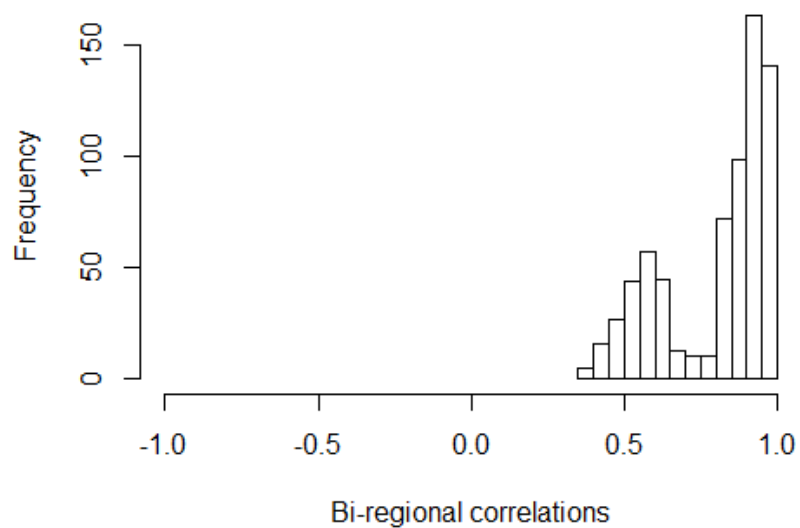
Table A10: Influence of cyclical variables on start-ups conditional on the four types using Hodrick-Prescott and Baxter-King filter in the same data set

Start-up rates in:	Type 1: non-innovative and small		Type 2: non-innovative and large		Type 3: innovative and small		Type 4: innovative and large	
	HP	BK	HP	BK	HP	BK	HP	BK
Unemployment rate – cyclical component $t - 1$	0.05**	0.06***	0.11***	0.10***	-0.03	-0.03	-0.02	-0.01
GDP – cyclical component $t - 1$	-0.18***	-0.17***	-0.01	-0.02	-0.19***	-0.20***	-0.05	-0.05
Share of employees in small businesses $t - 1$	-0.05	-0.06	-0.09***	-0.10***	0.12***	0.11***	0.15***	0.15***
Share of employees with tertiary education $t - 1$	-0.10**	-0.10**	0.04	0.03	-0.05**	-0.05**	-0.12***	-0.12**
Number of professors per 1,000 workforce $t - 1$	0.02	0.02	0.02	0.02	0.02	0.03	0.01	0.02
Number of patent applications per 1,000 workforce $t - 1$	0.04	0.05	-0.03	-0.03	0.06***	0.06***	0.10**	0.10**
Constant	-0.65***	-0.64***	-0.24***	-0.23***	0.32***	0.33***	0.52***	0.52***
R ²	0.63	0.62	0.76	0.76	0.70	0.70	0.46	0.46

Notes: Fixed effects panel estimates. ***, ** statistically significant at the 1 percent and the 5 percent level, respectively. Business cycle is the cyclical component of the Hodrick-Prescott filtered (HP) or Baxter-King filtered (BK) variables, where the same observations are used in the estimation procedure. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 411 (due to filtering values at the beginning and the end of a time series are lost) in all models.



(a) GDP cycle



(b) Unemployment cycle

Figure A1: Bi-regional correlations between GDP and unemployment cycle

Appendix B: spatial error model

To test whether our results are sensitive to including unobserved spatial dependencies, we estimate the following spatial error model with spatial fixed effects:

$$\text{Startup rate}_{i,t}^{\tau} = \mu_i^{\tau} + \alpha_1^{\tau} \text{BC unemployment}_{i,t-1} + \alpha_2^{\tau} \text{BC GDP}_{i,t-1} + \boldsymbol{\eta}_{\tau}^{\top} \mathbf{x}_{i,t-1} + su_{i,t}^{\tau} \quad (\text{B1})$$

The main difference between the model in (6) and (B1) is that instead of a simple error term $u_{i,t}^{\tau}$, we now have a spatially lagged error $su_{i,t}^{\tau}$. Suppressing the type indicator for notational convenience, the spatial error is constructed as follows:

$$su_{i,t} = \zeta \sum_{j=1}^N w_{i,j} su_{j,t} + \varepsilon_{i,t}$$

where $\zeta \in (0,1)$. Thus, the effect in region i depends on the weighted effects from all other regions $\sum_{j=1}^N w_{i,j} su_{j,t}$ and a region-specific effect $\varepsilon_{i,t}$. The weights are constructed in two steps. In the first step, two regions with a common border are assigned a weight of 1 such that

$$\tilde{w}_{i,j} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ have a common border} \\ 0 & \text{if no common border or if } i = j \end{cases}$$

while regions without a common border are assigned a weight of 0. In the second step, weights are normalized such that they sum up to 1: $w_{i,j} = \tilde{w}_{i,j} (\sum_{i=1}^N \tilde{w}_{i,j})^{-1}$. The model in (B1) is estimated with maximum likelihood, as suggested by Elhorst (2003).

Table B1: Influence of cyclical variables on start-ups with spatially lagged errors

Start-up rates in:	Type 1: non-innovative and small	Type 2: non-innovative and large	Type 3: innovative and small	Type 4: innovative and large
Unemployment rate – cyclical component $t - 1$	0.05	0.08**	0.01	0.09**
GDP – cyclical component $t - 1$	-0.07**	-0.05	-0.10***	-0.01
Share of employees in small busi- nesses $t - 1$	-0.02	-0.03	0.03	0.09**
Share of employees with tertiary education $t - 1$	0.00	0.01	-0.01	-0.04
Number of professors per 1,000 workforce $t - 1$	-0.01	0.02	0.01	0.02
Number of patent applications per 1,000 workforce $t - 1$	0.03	0.01	0.04	0.09***
Spatial error coefficient (ζ)	0.67***	0.46***	0.44***	0.49***

Notes: ***, ** statistically significant at 1 percent and 5 percent, respectively; fixed effects estimation with spatial errors; business cycle is the cyclical component of the Hodrick-Prescott filtered variables. The remaining independent variables are included in growth rates. All variables are lagged by one period. The number of observations is 494 (38 cross sections, 13 years) in all models.