Master Thesis U.S.E.

The irrational process of private market innovation[1]

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Abstract: Private market innovative efforts, through the channels of firm R&D and entrepreneurship, play a major role in technological advancement and the endurance of comparative advantages of an economy. The success rate and efficiency with which such efforts can be executed is likely correlated with the economy's position along the business cycle. Economic confidence sentiments ('Animal spirits') have been shown to affect the strength of the business cycle movements. This study aims to examine whether such sentiments affect private market innovative efforts both indirectly, through this effect on the business cycle, as well as in a direct way controlling for the business cycle effects. Quantitative analysis on a dynamic panel dataset of 12 EU member states using both a Fixed-effect model with Driscoll Kraay standard errors, as well as an Arellano-Bond GMM model is performed. The individual results for entrepreneurship and R&D are somewhat mixed, however when combined, signs of a significant and sizable effect seem to emerge. Such findings seem to be a novelty within the literature and could help improve the innovation-targeting policy efforts of governmental institutions as well as our broader understanding of the interrelatedness of economic and societal phenomena.

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Introduction

Innovation lies at the heart of human progress. It feeds the change, development and growth of our culture, society, and economy. Within the field of economics, it is seen as the driving force of competitive advantages (Audretsch et al., 2020). Innovation cannot be studied in a vacuum, and various literature streams are still exploring the various ways (macro-) phenomena might affect innovative efforts and success rates.

Ever since Adam Smith's influential 'The wealth of nations', one often finds the private market as the purest source of efficient outcomes in economic theory. This piece will focus on the effects of innovation that is initiated by the private market through either research & development (R&D) of existing ventures or the process of new venture creation (entrepreneurship), which are the primary sources of private innovation (Francois & Lloyd-Ellis, 2003).

Economic growth is seen as the primary mode of transportation on the road towards improved welfare and wellbeing. This development path however is not a continuous line but shows strong cyclical tendencies with periods of 'booms' and 'busts' (or recessions) following one another – a phenomenon commonly known as the 'business cycle'. The state of the business cycle naturally affects the economic opportunities at hand for both established firms and entrepreneurial endeavors, thus likely affecting innovation through these channels.

In basic economic theory and modelling, the concept of the homo economicus is often assumed – the all-knowing perfectly rational economic agent. In line with this, a substantial amount of modelling was based upon the notion of 'rational expectations', or agents being able to rationally form expectations of the future based upon all publicly available present information. However, this is of course nothing more than a theoretical construct. Economic history shows a strong cyclical tendency of people going out and buying assets whenever they are confident (known as a 'bull market' in finance); and when they are unconfident they withdraw and sell ('bear market' in finance). Humans seem to have 'irrational' tendencies that can steer (economic) behavior based upon cyclical movements in confidence.

Since human behavior lies at the heart of economics, such 'irrational' tendencies or sentiments can have serious consequences for our ability to understand and ultimately predict human economic behavior (De Grauwe, 2012). The collective term often used for such irrational tendencies or sentiments is 'animal spirits', as introduced by Keynes in 1936, referring to irrationally strong sentiments of either positivism or pessimism in collective behavior. Such 'irrational' sentiments can possess strong self-fulfilling tendencies (Keynes, 1936), and seriously affect the business cycle through their 'contagion effect' on other agents (De Grauwe, 2012). These findings would suggest that these 'irrational' sentiments likely affect (private) innovation indirectly through their effect on the business cycle. Controlling for this indirect effect, could there be a direct effect of animal spirits on private innovation? This question forms the basis of this thesis' two-stage research question:

(a.) *What is the effect of animal spirits on private firm R&D and Entrepreneurship through the business cycle?* (b.) *Do animal spirits affect private innovation directly, controlling for the effect through the business cycle?*

Where part (a.) is based on a combination of currently suggested relationships in the literature, upon which (b.) is build as a novel conceptualized relationship to be tested.

This piece will be structured as follows: first the two major sources of private innovation will be introduced (R&D and entrepreneurship). Building upon that, the trajectory trends of both will be observed with a specific focus on the overarching cyclicality in the (modern) economy and its potential influence on both sources. Once that has been formulated, the concept of irrational sentiments affecting the cyclical movements in the business cycle will be introduced to the model to ultimately attempt to map the effect of irrational sentiments on private market innovation through the business cycle. The final step will be to see if animal spirits still affect private innovation, controlling for their indirect effect through the business cycle.

Quantitative analysis of the different elements and their relative explanatory power will be applied in the form of both a Fixed effects model with Driscoll & Kraay standard errors, as well as an Arellano-Bond GMM regression model. The aim of this quantitative aspect is to further illustrate and study the conceptualized and described trends and relationships of the earlier chapters. The tested relationships and their various steps are drawn out below for further clarification (figure 1.1):

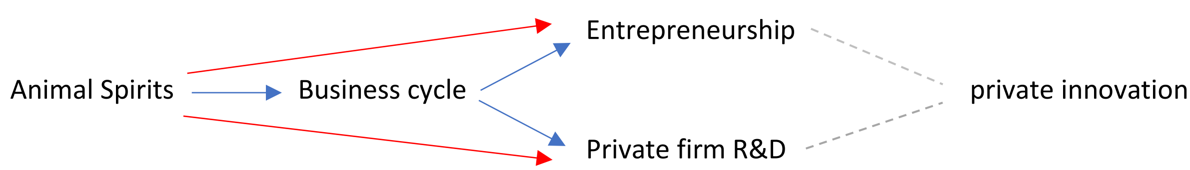

Figure 1.1: *with research question (a.) in blue arrows, and (b.) in red arrows.*

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Literature review

2.1. The relevance of private innovation

If one dives into the broad realm of literature surrounding the concept of innovation, one often stumbles upon the work of Joseph Schumpeter. In the first half of the 20th century, he developed the now often heralded concept of 'creative destruction' of innovation and its (economic) effects. His work on innovation is one the cornerstones upon which a lot of future researchers build their work. He sets out the following definition:

> "Innovation is the market introduction of a technical or organizational novelty, not just it's invention" (Schumpeter 1911, p. 109)

Suggesting that innovation only emerges after a dual-step procedure of invention and bringing to market of this invention. Schumpeter hence draws a sharp conceptual distinction between innovation and invention, claiming inventions to be 'economically irrelevant' as long as they are not carried into practice. Thus, innovation in particular must be distinguished from 'invention' (Swedberg, 1992).

An often-applied proxy for measuring innovation is historical patenting data. The reasoning being that firms will only undertake the costly and time-consuming process if they themselves deem their product innovative enough to be worth the effort, with the granting of the patent as an independent confirmation of its originality. Such a measure can work well for certain technical and industrial sectors but is found to be more limited in its capabilities to capture innovation in non-tangible service-related innovations (Francois & Lloyd-Ellis, 2003). The literature is mixed with different findings for different sectors (see e.g., Archibugi, 1992; Smith, 2005). Since we want to prevent controversy and be able to capture a broad range of innovation, we will not include patenting trends in our analysis.

This study will focus on the sources of private innovation instead, where we assume that more investment and/or activity in the sources naturally proxies for more innovation output over time. There are two main sources of private innovation, either existing firms adapting through investments in R&D or new firms' creation through (innovative) entrepreneurship (Francois & Lloyd-Ellis, 2003). The following chapter is meant to add context and background to the terms studied, the most important (summarized) information is usually to be found in the first and last paragraph of each section.

2.2. Research & Development

Research and development (R&D) helps existing firms to maintain a level of competitiveness. Total R&D effort has long been seen in both academic and popular literature as a key indicator and determinant of the technological progressiveness of firms, industries and even nation-states (Cohen & Klepper, 1996b).

Fully public-funded research institutions and universities can be important sources of knowledge advancement too, but are excluded in this study, for we are focusing ourselves on private market innovation. We cannot however, discriminate between solely privately funded R&D and R&D expenditures that received some form of subsidy, tax benefit or other (non-monetary) benefits or government intervention, for they are too intertwined to allow for any meaningful attempt of disentanglement.

An entire literature stream is devoted to the question whether and to what extent the government should support private market R&D (e.g., Nelson, 1959; Krugman, 1987; Romer, 1990). The main line of reasoning being that private players will invest below the publicly optimal amount in R&D since they cannot fully recoup their investment, with market failures such as spillover effects, financial constraints, uncertainty, and risk aversion further reducing private funding of R&D. R&D subsidy is seen as a policy tool explicitly designed to help firms undertake socially beneficial private R&D (e.g., Aerts and Schmidt, 2008; Li, 2012; Meuleman and De Maeseneire, 2012).

Although the market failure theory justifies government R&D subsidy, one major concern in the literature is that the theory is not very clear on whether the government can identify R&D projects that are subject to market failure (Choi & Lee, 2017). Discussions surround the question whether government R&D subsidy might simply support private R&D projects that would have been undertaken even without a subsidy and might just crowd out private R&D (e.g., David et al., 2000; Dimos and Pugh, 2016), or how effective a dollar of subsidy is in generating corporate R&D (Wolf and Reinthaler, 2008). Governments can have a steering role in subsidizing R&D with larger societal benefits in specific areas (e.g., semiconductors, drug development). To be successful at such endeavors, the relevant agencies would need an adequate level of expertise in the relevant R&D fields (Choi & lee, 2017), in order to properly clarify the objectives and designs of the research programs. Such discussions on the public-private subsidy debate go beyond the scope of this study, but they do offer some interesting perspectives for policy considerations.

Within the private market a sort of paradox seems to exist where firms that first develop successful product innovations are not necessarily the firms that ultimately reap the profits (Choi & Lee, 2017). Examples of this can be found in all types of industries throughout history (e.g., typewriters, automobiles, telecommunication). In contrast, Cohen and Klepper (1996a, b) suggest that firms can appropriate returns from process or incremental product innovations with relative ease because the firms enjoy higher profits from simply lowering production cost or improving the quality of existing products. Thus, suggesting a benefit for the bringing to market of smaller incremental steps in the development cycle.

Econometric evidence seems to overwhelmingly support the notion of a positive rate of return to R&D investments at both the private and social levels (David et al., 2000). R&D expenditures rise proportionately with firm size in most industries, while the number of patents or innovations generated per dollar of R&D expenditure declines with firm size. Cohen and Klepper (1996a) show how these patterns can be explained by the idea that large firms can perform 'R&D cost spreading', by spreading out the fruits of their R&D over a larger level of output. This implies increasing private returns to firm size in R&D, which can help to explain observed patterns in international trade (Krugman, 1979) and macroeconomic growth (Romer, 1986). R&D cost spreading would imply that the relationship between R&D and size should be weaker for those industries and types of R&D where either innovations are more saleable, or where the prospects for rapid growth due to innovation are stronger.

Increasing firm sizes only confer a potential advantage and can have the economic downside of inducing welfare costs through monopolistic power (Cohen and Klepper, 1996a). Small firms too can play a key role in advancing technology and might possess key distinctive R&D capabilities which help them to coexist with or even outpace larger firms (Cohen and Klepper, 1996a). One way to consolidate the positives, while remaining the advantages of a competitive market, is R&D cooperation. R&D

cooperation can reduce R&D costs per unit of output and enable firms to profit from R&D projects that they could not profit from alone. This has been successfully implemented in a number of ways, like the government coordinated cooperation in Japan during the 80's (Fransman, 1990), or the relaxation of antitrust regulations in certain sectors in the U.S. (Scott, 1989). Noteworthy as it may be the discussion around the exact scope and way governments may best steer R&D, again, lies out of the realm of this study.

Concluding, the exact way to optimize firm R&D seems to still be up for debate. With theories arguing for benefits of either larger firms, who can reap the fruits of cost spreading, or smaller firms (e.g., entrepreneurship) which have the flexibility and agility required to undertake daring endeavors. No literature, nor policymaker, however, seems to deny both the potential positive role for the government in innovation (if executed properly) and most certainly the significantly positive contribution of firm led research and development for economic growth and competitiveness as well as technological and societal advancement (Cohen & Klepper, 1996b). This process can either be performed by (large) established firms or be undertaken by newly created ventures.

2.3. Entrepreneurship

The literature sees entrepreneurship as the act of new venture creation, 'making something out of nothing'. It is seen simultaneously as the result and mediator of evolution (Day, 1987): entrepreneurial behavior as an output is enabled by the system, while the new value created, and potential structural change as an outcome of the system is mediated by entrepreneurship.

> "Productive entrepreneurship" refers to "any entrepreneurial activity that contributes directly or indirectly to net output of the economy or to the capacity to produce additional output" (Baumol 1993, p. 30).

What makes entrepreneurship innovative and/or productive? Productive entrepreneurship is usually considered to be high-growth entrepreneurship: young, owner-managed firms that have been able to grow beyond a certain (financial) threshold. Productive entrepreneurship has been shown to contribute to economic growth (e.g., Bosma et al., 2018). Recent publications, like Wurth et al. (2021), call for a 'opening up' of the concept to also include social and ecological value creation that is hard to directly measure in monetary terms. However, literature is still rather puzzled on how to quantify such measures to a level where they would be fit for proper comparative quantitative analysis.

According to Audretsch et al., (2020) only a small share of start-ups is innovative, but those who are can play a particularly important role for economic development, technological advancement, and societal impact. Policy thus often aims to promote the development of such innovative ventures, promoting the birth of start-ups. In practice such policies, without a tight scrutiny of start-up quality often result in a 'bad public policy' (Audretsch et al., 2020) [essentially: many start-ups fail, and of those which do succeed a lot turn out to be not so innovative, and of those which do turn out to be innovative a lot do not manage to grow to a 'high impact firm']. Audretsch et al. (2020) continue to explain how a view of 'innovativeness' as a fixed stamp on a firm could be a severely short-sighted view. Based on an analysis of 39 different in-effect entrepreneurship policies, they make an attempt to build a multi-staged framework for measuring innovativeness of start-ups based upon the stage the venture is in in its development path. They highlight the necessity of different approaches for firms in different stages of their development cycle, finding that a 'one size must fit all' approach often lacks in efficiency outcomes.

The industries in which start-ups operate and the degree to which they can develop are determined to a large extent by the conditions of the regions in which entrepreneurs and start-ups operate' (Acs et al., 2017; Alvedalen and Boschma, 2017). Such results thus suggest a strong societal contextual or cultural aspect in entrepreneurship productivity and innovation.

Cultures naturally differ between regions and communities, a phenomenon widely described in its own research brances (e.g., Hofstede, 1980; Tabellini, 2010; Obschonka et al., 2018; Huggins and Thompson, 2021). Culture is often defined as the collective programming of the mind, distinguishing one group from another, and refers to beliefs and values that are transmitted within groups over generations (Guiso et al., 2006). The effects for specific regions depend on industrial and cultural history (e.g., Huggings et al, 2021) that over time have a tendency to become 'imprinted' in local culture (Marquis & Tilcsik, 2013). This in turn can change the local circumstances in which innovation is to emerge through policy. Hence the context should always be taken into consideration when studying or formulating detailed policies for specific regions (e.g., Leendertse et al., 2021).

The local cultural aspects of a region are often reflected in their local institutions. Entrepreneurial literature has steered towards a paradigm in which the entrepreneur is seen as being part of a multi-faceted 'Entrepreneurial ecosystem', of which their institutional environment is one element. The different elements are theorized to have a high level of inter-layer causation or interdependence among each other with both upward and downward causation over time creating natural feedback mechanisms (Stam, 2015; Stam & Van de Ven, 2019). Wurth et al. (2021) further explain how this "recursive continuous process" of interaction between ecosystems (context), processes, and outputs/outcomes shape the ecosystem and the conditions for entrepreneurs. The notion of Ecosystems is not an absolute but an artificial unit of analysis here, which can have a stimulating effect on entrepreneurial activity.

Entrepreneurial activity is not limited to a particular territory. However, ecosystems often have a clustering effect on entrepreneurship presence (e.g., Garsney & Hefferman, 2005). Stuetzer et al., (2016) approach the cluster phenomenon by theorizing that a historically high regional presence of large-scale firms negatively affects entrepreneurship, due to low levels of human capital and entrepreneurial skills, fewer opportunities for entry and entrepreneurship inhibiting formal and informal institutions. Stuetzer et al. (2016) find significant explanatory effect of historical (18th century) coal-field proximity, as a proxy for industrialization, for current low levels of entrepreneurial activity in the UK – supporting their theorized effects. These effects can become self-perpetuating over time, ultimately resulting in persistent low levels of entrepreneurship activity and entrepreneurship culture (Huggins et al., 2021). This would suggest that regional prevalence of small firm employment is positively related to regional start-up activity and vice versa.

Leendertse et al. (2021) made a serious attempt to quantify the Entrepreneurial ecosystem concept to a level where it could reliably be used for inter-regional as well as time-series analysis. They developed the 'Entrepreneurial ecosystem index', which essentially summarizes the local strength of the ecosystem elements model as introduced by Stam (2015) and others into a one variable index. Leenderste et al. (2021) created a ranking of European regions that seems to hold a credible range of variation as well as external validity. These metrices could potentially be used to correct for regional and/or contextual differences in predicting entrepreneurial output effects of the business cycle in future studies, but currently lacks the variation over time required for this study.

The consensus of the recent entrepreneurship literature seems to thus hinge around the idea that an individual cannot be studied in isolation of the contextual (or 'systemic' as in Stam, 2015) conditions it faces. These conditions can have far-reaching and historically long-lasting effects in determining both the emergence, quantity, and quality/success rate of entrepreneurial endeavors.

Summarizing, entrepreneurial activity creates value through new-firm creation, in its most basic form any positive value creation is seen as 'productive entrepreneurial activity'. Despite recent literature calling for a wider, more inclusive definition, monetary measures still seem to be the most reliable method of quantifying entrepreneurial output. When trying to predict and/or optimize entrepreneurial output, the contextual or 'systemic' elements should be taken into account as an interrelated whole or 'ecosystem'. The majority of entrepreneurial activity is not innovative, and innovativeness should not be treated as a fixed 'stamp', but rather as a fluid and broad concept that can evolve and/or disappear over a firm's development path.

2.4. Economic cyclicality

Economic growth is the backbone of modern policy and the driving force of equity markets. Are the recurring recessions of the capitalist world merely short-term adjustments to changing economic circumstances in a system that tends, in general, toward a form of growth equilibrium? Or does the economy follow some sort of cyclicality, known as the business cycle, along its development path? Empirical evidence seems to suggest the latter.

Economic cyclicality is commonly measured in the form of the 'output gap', or the deviation of actual GDP growth from its potential (or sustainable) growth pattern (essentially a complex moving mean based on historical data and assumptions). Deviations from this growth path are seen as the shocks, or 'booms and busts' of the business cycle. Models using the historical output gap find that business cycle movements are characterized by periods of tranquility interrupted by large positive and negative movements in output, in other words, booms and busts with a strong auto-regressive nature and non-normal distribution over time (e.g., Fagiolo et al. 2008, 2009; De Grauwe, 2012). Such models do not come without controversy however, main points of criticism surround the fact that the 'potential output' can only be calculated ex-ante and is conditional to a variety of assumptions which do not necessarily reflect real-world conditions.

Academics have been attempting to model the business cycle for decades. The commonly described pattern in quantitative models shows how an average cycle starts with a growth spurt which is then followed by a growth slowdown before the economy enters a period of relatively constant decline during the downturn (e.g., Sichel, 1993; Balke & Wyne, 1995; Francis & Lloyd, 2003).

Within the modelling literature we saw a strong popularity of the real business cycle (or RBC) models in the past (e.g., Cooley & Hansen, 1989; Farmer & Guo, 1994; Balke & Wyne, 1995) with the New Keynesian model currently being the canonical model of business cycles (De Grauwe, 2012; Gali, 2015). This New Keynesian model too is challenged and/or expanded upon on a regular basis (e.g., Michaillat & Saez, 2022). Fierce discussions have been held on which elements affect the cyclicality at what level in what way, and which elements should thus consequently be included in econometric modelling of the business cycle.

The details of such discussions naturally go beyond the scope of this study, however what does seem to emerge is an academic consensus on the notion that the economy indeed, as further supported by historical data, shows strong cyclical tendencies. These tendencies show patterns of booms, slowdowns, and busts, and are interlinked with the economy's longitudinal growth process (Francis & Lloyd, 2003). We will follow the broader consensus and measure economic cyclicality in the form of the output gap.

2.5. The effect of economic cyclicality on private innovation

One would naturally expect such cycles of 'booms' and 'busts' likely effect the outcomes and potential success rates of private market innovative efforts. In a survey of U.S. manufacturing plants, Fay and Medoff (1985) find that during a trough (or 'bust') quarter the typical plant paid for about 8 percent more labor hours than technologically necessary. Only half of this was attributed to hoarded labor [due to the high costs of acquiring/firing workers]—the remainder was used in other productive activities. Of the respondents that reassigned workers during recessions (more than half of respondents), about one-third allocated them to "reworking output" and another third to "training", thus suggesting that a significant portion of labor no longer required for production purposes was in fact redirected to research and re-educational purposes i.e., research and (human capital) development.

Several authors have argued that recessions should ideally promote a range of such activities that will contribute to growth through long-run productivity (e.g., Barlevy, 2007). This view rests on the notion that the opportunity cost of achieving productivity growth—the forgone output or revenue that could have been achieved instead—is lower in recessions, providing a logical incentive to undertake such activities in downturns.

Measured R&D activity, however, seems to be procyclical (i.e., it grows and shrinks in tandem with the movements along the business cycle). Schmookler (1966) first suggested a basic procyclicality of patenting, a finding later supported by studies like Geroski & Walters (1995) and Griliches (1990). Since patenting is often used as a proxy to measure innovation, would such results suggest a procyclical character of the sources of private innovation too. Such a finding would be surprising, since R&D seems like an activity that should similarly be concentrated in recessions: it is labor intensive, and while labor productivity in producing goods appears to decline in recessions, work studied in Griliches (1990) suggests productivity in innovation is acyclical in nature.

Fatas (2000) finds that growth in real R&D expenditures in the United States is positively correlated with real GDP growth. However, these studies don't make a hard distinction between publicly and privately funded research and development. If we solely focus on privately funded R&D and distinguish between basic research, which is not generally driven by commercial considerations (and is a small proportion of the total), and applied research, which is, then this stylized fact is not so clear. Along a similar line of reasoning Francois & Lloyd-Ellis (2003) conclude that there is in fact no significant correlation between growth rates in real applied research (NSF data) and real GDP for the United States over the period 1953 to 1999.

Post 1945 cross-country evidence suggests a strong and significant negative partial correlation between volatility and growth, after controlling for common growth correlates (e.g., Ramey & Ramey, 1995). This correlation is economically significant even among OECD countries (Francois & Lloyd-Ellis, 2003). Severe volatility introduces uncertainty to the market, and technologically successful new products might not be adopted in the market because of market uncertainty (Eggers, 2012; Hellmann and Perotti, 2011). Volatility is most observed in periods of booms and bust, thus suggesting a link between the state of the business cycle, economic growth, and the bringing to market of innovation. The observed effects also introduce another interesting causal relationship: the effect of (market) uncertainty, or sentiment on innovation and economic growth, how strong of an effect can such sentiments of uncertainty have, and what potential consequences might they carry?

2.6. Irrationality through 'Animal spirits'

Business cycles are not smooth and rational, but rather resemble tendencies of booms and busts, which are theorized to get strengthened by irrational emotional sentiments, a concept dubbed *animal spirits*. Accepting the 'animal spirits' phenomenon would mean that such sentiments consequently are likely to affect innovation cycles through their strengthening effect on the business cycle. Economic (often consumer focused) sentiment indexes are seen as the main method of quantifying sentiments, and hence will be used in this study too in order to quantify animal spirits (see e.g., De Grauwe, 2012).

The concept of animal spirits can be traced back to its ancient and medieval Latin form, *spiritus animalis*, where the word *animal* means "of the mind" or "animating". It refers to a basic mental energy and life force. In modern economics *animal spirits* refers to a 'restless and inconsistent' element in the economy. It refers to our peculiar relationship with ambiguity or uncertainty. Sometimes we are paralyzed by it. Yet at other times it refreshes and energizes us, overcoming our fears and inability to make decisions. Akerlof & Schiller (2009) explain:

> "Just as families sometimes cohere and at other times argue, are sometimes happy and at other times depressed, are sometimes successful and at other times in disarray, so too do whole economies go through good and bad times. The social fabric changes. Our level of trust in one another varies. And our willingness to undertake effort and engage in self-sacrifice is by no means constant." (p. 4)

The concept of animal spirits was introduced to economics by Keynes (1936). Keynes defined it as waves of optimism and pessimism of investors which have a self-fulfilling property and can drive the movements of investment and output. The notion itself has had a bit of a cyclical tendency, falling out of grace in the 1970's-90's, after which it was revitalized by influential studies and publications like e.g., Farmer & Guo (1994), Francois & Lloyd-Ellis (2003), Akerlof & Schiller (2009), among others. Over time, multiple definitions of animal spirits have been coined by various researchers of different segments of the economic sciences (see Akerlof & Schiller, 2009).

The overall notion of an unseen force propelling the economy, driving it into booms and busts, is nothing new. W. Bagehot in his 1873 book *Lombard Street* already remarks that in a period of economic recovery, it seems as if business "leaps forward as if by magic":

> "Most people who begin to think of the subject are puzzled… Why should there be any great tides of industry, with large diffused profits profit by the way of flow, and large diffused want of profit by way of ebb? The main answer is hardly given distinctly in our common books of political economy. These books do not tell you what is the fund out of which large general profits are paid in good times, nor do they explain why that fund is not available for the same purpose in bad times" (Bagehot (1920 [1873], pp. 144, 119).

Suggesting a puzzling attitude towards the flows of business cycles and capital availability, here worded as 'funds', out of which profits are paid, but which cannot be attained to hamper crisis in downtimes. This question still seems to puzzle people to this day, with news media often lacking explanations that go further than the key economic indicators. An example would be the measures following the 2008 financial crisis and the swift initial recovery of a far greater size than the value of the packages as implemented by the authorities (Akerlof & Schiller, 2009). An even more recent example would be the large economic and stock-market bust during the start of the 2020 covid-19 pandemic, followed by remarkably swift recovery numbers and asset price increases far beyond the pre-pandemic levels. Do such nascent recoveries merely reflect a new willingness to spend all over the world, as suggested by many popular accounts, as if that is a primordial force of the economy that defies any further analysis? Or are there other forces driving the economy at play?

In their 2009 publication on Animal Spirits, Akerlof & Schiller explain how the understanding of such drivers lies somewhat outside the traditional boundaries of economic research, in the realm of psychology. The recovery after the 2008 financial crisis, they argue, defies the analysis of many economists who build structural econometric models and see the sudden recovery as the result of "error terms" or "residuals" or "innovations" in their equations. It defies the analysis of those economists of the "real business cycle" persuasion, who are in the habit of thinking that all economic fluctuations are ultimately driven by exogenous changes in "technology" and "productivity" but cannot point to a description of the cause of such a change as observed right after the 2008 financial crisis (Akerlof & Schiller, 2009).

Fundamental to most modern forms of economics is the natural tendency to come towards an equilibrium of supply and demand, as first formulated by Adam Smith's famous notion of the 'invisible hand'. Market clearing and rational expectations have been accepted by a lot of modern researchers as being key elements of theories around economic fluctuations (Farmer & Guo, 1994). Adam Smith's (or classical economic) theory, however, seemingly fails to describe why there is so much variation in the economy. In any model with rational agents, the value of an asset will equal the net present value of the flows that arise from owning it (Farmer, 2011). Such a model does not explain why the price of an asset, or even the economy at large "takes rollercoaster rides". For one would expect relative stability once the economy has converged towards aforementioned equilibria over time. Rational behavior should prevail based upon logical processing of all publicly available information, yet we can observe strong variation and patterns of cyclicality in things such as asset prices, employment, and overall economic output.

Akerlof & Schiller (2009) identify a total of five concepts and phenomena which build up their notion of 'animal spirits'. They introduce the notions of 'fairness', 'corrupt and anti-social behavior', 'stories', 'money illusion' and 'confidence', with the latter two being the most important ones according to the authors. They see these concepts as a factor to help create a bridge between harder economic theory and actual commonly observed behavior in practice. They identify confidence and the feedback mechanisms between it and the economy that amplify disturbances as the cornerstone of their theory. This fits the larger consensus on the identity of animal spirits as being most easily identified as swings of confidence (e.g., Farmer, 2012), and will thus be the aspect we will focus on in this study.

Recessions were seen in the past as a necessity to "restore confidence", ever since the founding of the US republic, business downturns have been proclaimed as the result of a loss of confidence (Akerlof & Shiller 2009). F.D. Roosevelt is famously quoted during the great depression as stating that: "The only thing we have to fear, is fear itself". With fear in this context representing a natural lack of confidence.

Economists have a particular interpretation of the meaning of the term *confidence*. Many phenomena are characterized by two (or more) equilibria. There may be a good equilibrium, in which we say that there is confidence. And there may also be a bad equilibrium, with no confidence. In this view there is nothing more to confidence than a prediction. A confident prediction is one that projects the future to be rosy; an unconfident prediction is one that projects the future as bleak.

However, if one looks up *confidence* in the dictionary, it is defined as more than a prediction. The dictionary says that it means "trust "or "full belief". The word confidence comes from the Latin *fido*, meaning "I trust". The 2008 financial crisis was also called a *credit crisis*. The word *credit* derives from the Latin *credo*, meaning "I believe". Thus, Akerlof & Shiller (2009) argue that the economic definition likely misses something. Sociologist Georg Simmel explains how the very meaning of trust is that we go beyond the rational, it is the mutual "faithfulness" (Simmel, 1978) on which all social relationships ultimately depend (Lewis & Weigert, 1985). To trust is to live as if certain rationally possible futures will not occur (Lewis & Weigert, 1985), a truly trusting person thus often discards or discounts certain information. She may not even process and/or act rationally upon the information she receives. She acts according to what she *trusts* to be true.

If this is what we mean by confidence, then we see immediately why, if it varies over time, it should likely play a significant role in the business cycle. In good times, people trust, they seemingly make decisions spontaneously. They know instinctively that they will be successful, so they suspend their suspicions. Asset values will remain high and might even be increasing too. As long as people remain trusting, their impulses will not be evident. But then, when the confidence disappears, the tide goes out. Or as Akerlof and Shiller (2009) put it: 'the nakedness of their decisions stands revealed'. A great example of trust suddenly disappearing was the uncertainty brought upon the world during the 2020 emergence of the covid-19 pandemic (see figure 2.1, where it is clearly visible for the year 2020).

When people are confident, they go out and buy; when they are unconfident they withdraw and sell (Farmer 2011). Economic history is full of such cycles of confidence followed by withdrawal. Standard economic theory describes a formal process for making rational decisions: people consider all the options available to them. They consider the outcomes of all these options and how advantageous each outcome would be. They consider the probabilities of each of these options. And formulate a decision based solely on such rational considerations (Ekelund & Hébert, 2013). This ties into the notion of the homo economicus – the perfectly rational all-knowing agent. But can we really be that? Do we really have a way to define what those probabilities and outcomes are? Or do we base our business decisions as well as personal decisions with regard to which assets to buy and hold more on the basis of whether or not we have a certain level of confidence? Many of the decisions we make – including some of the most important ones in our lives – are made because they "feel right" (Akerlof & Schiller, 2009). John F. Welch, the long-time CEO of General Electric, for example claims that such decisions are made "straight from the gut" (Welch & Byrne, 2001) But at the level of the macroeconomy, confidence seemingly comes and goes. Sometimes it is justified, sometimes it might not be, it is not just a rational prediction.

In his highly influential 1936 'The General Theory of Employment, Interest and Money' John Keynes sought to explain departures from full employment, and he emphasized the explanatory relevance and importance of animal spirits. Since the future is so hard to predict, decisions seemingly are the result of "a spontaneous urge to action". They are not, as rational-agent oriented economic theory would dictate, "the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities." Keynes (1973 [1936], pp. 149-150, 161-62).

Based upon this highly influential publication, Hicks (1937) worked out the concept of the Keynesian multiplier. This multiplier has been a cornerstone in economic teaching ever since, explaining how each dollar spent by the government is repeatedly multiplied by consumers at a certain fraction known as the marginal propensity to consume (MPC). This repetitive multiplication does not go on indefinitely, but to the level 1/(1-MPC). The multiplier theory explained how a small dip in expenditures can have a great magnifying effect – if there were a small but substantial decline in consumption expenditures because people overreacted in fear to a stock market crash, such as the one of 1929, then this would act just like a *negative* government stimulus. A depression could come about over the course of several years, as the multiple rounds of negative expenditure hits put businesses further and further into the red (Hicks, 1937).

Keynes' multiplier theory won popularity among both policymakers, who started implementing it due to its ease of understanding and strong (perceived) explanatory power, as well as econometricians, who liked its ease of quantifiability (Akerlof & Shiller, 2009). To this day the US and other major governments still produce national income and consumption data in accordance with the demands of this theory. The creation of such datasets led to the creation of large-scale econometric models and simulations by laureated economists like Tinbergen (1936) and Klein (1940) on both national and intra-national levels. Keynes himself was skeptical of such models, for they only have a minimal role for animal spirits (Akerlof & Schiller, 2009).

Akerlof & Shiller plead for a 'confidence multiplier', that represents the change in income resulting from a one-unit change in confidence – 'however it may be conceived or measured'. An often-used measure is the Michigan Consumer Sentiment Index, but there are plenty others available (e.g., from the CBS for the Netherlands, or the aggregated EU sentiment indexes, as will be used later in this study). Causality tests for several countries suggest that current measured "confidence" does feed future GDP, and this result would seem to confirm the feedback implicit in Akerlof and Shiller's notion of the confidence multiplier. They see confidence as one of the key elements of animal spirits. We will use such a notion, in the form of the 'European Sentiment Indicator', in our following attempt to quantify the theorized relationship of animal spirits affecting private innovation.

To get a first broad feeling of the types of trends such an ‘sentiment indicator’ might show, and whether we can observe the “swings of confidence” described in this chapter in historical data, monthly European sentiment indicator (ESI) was corrected for seasonality (see Appendix 2.1) and plotted over time for illustrative purposes:

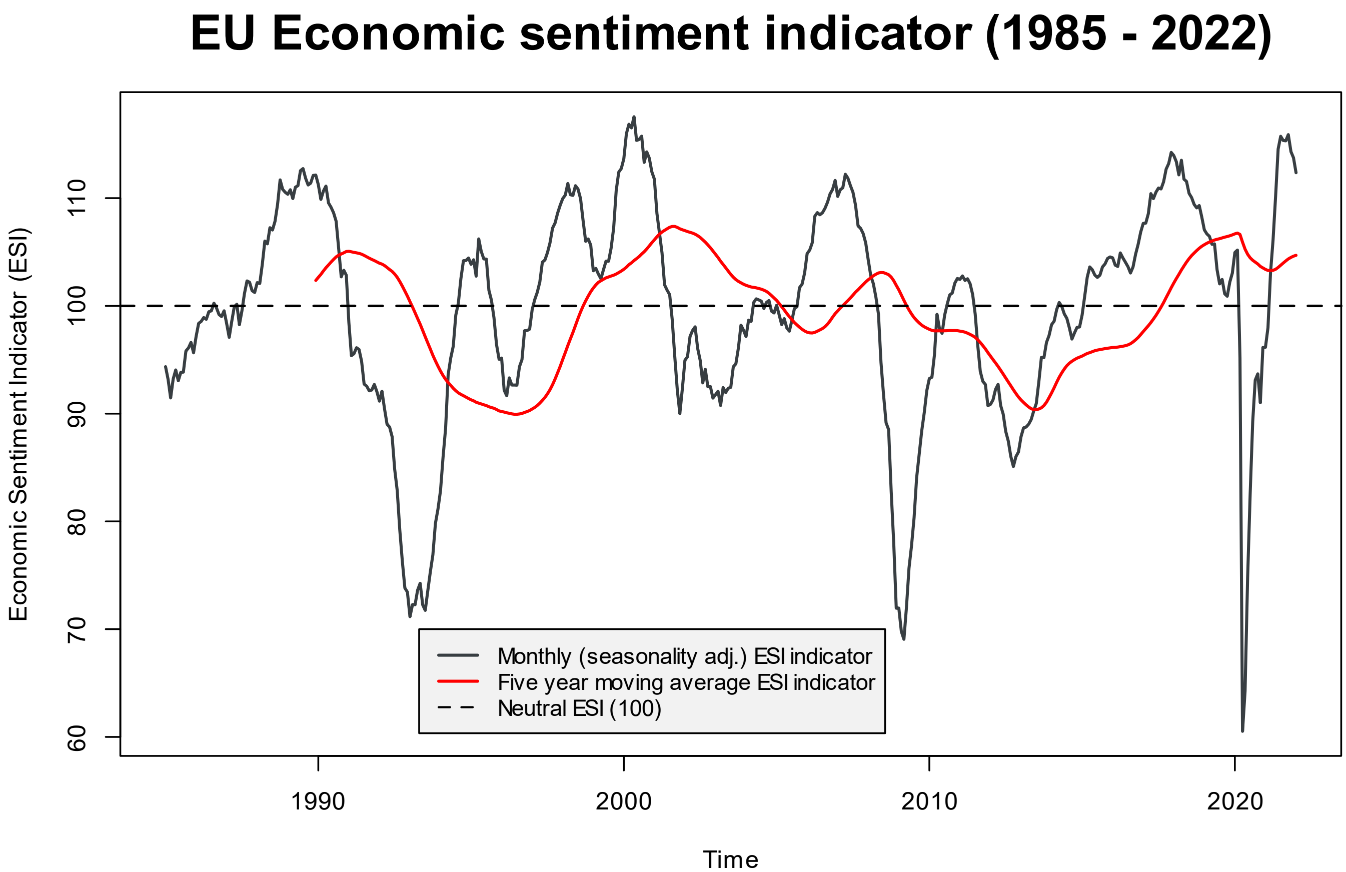

Figure 2.1. *Note: the time frame and reporting frequency differ from those used in later sections (see 3.5)*

Where one can visually examine strong and seemingly abrupt ‘confidence swings’ along known dips in the economic growth patterns as e.g., the 2002 ‘dot-com bubble’, the 2008-2009 financial crisis or the 2020 covid-19 pandemic. Such observations give us visual hints of an interrelationship between both.

Earlier simulation work by Farmer & Guo (1994) shows that not only that animal spirits can indeed drive business cycles, but that the phenomenon can occur in a model that is close enough to be compared quantitatively with the real business cycle paradigm. De Grauwe (2012) expands on this by finding significant effects of animal spirits on GDP output fluctuations in his simulation exercises based upon historical data on the United States. Combined, such findings naturally spark a desire for further research whether such effects also translate to an effect on private market innovation, an attempt at which will be made in the following chapters.

Data

In order to quantitatively test whether the theorized relationships of figure 1.1 (see introduction) exist, multiple datasets were collected for the time-period of 2005-2020. We'll start by discussing the region of study and sample period, after which each individual dataset will be introduced in this chapter, along with its general statistics. Some datasets had sub-annual reporting frequencies (e.g., monthly), if this was the case annual aggregates were constructed by taking the mean value of all months included in the respective reporting period as the variable value for that year

3.1. Sample area

The United States is an often-used area of analysis due to (among other things) it's significant economy, territorial coherency over recent times and ample data availability and publication history. The economic growth patterns of the United States have been described in great detail and quantities. However, the plentiful focus on the US does raise questions of generalizability and applicability of found results for other regions.

To offer an alternative perspective, the European union was selected as a unit of analysis for this study. Through its more turbulent and expansionary (recent) history, as well as complex inter-state structure, it lacks the longitudinal stability of the United States, and has such seen a more limited scope of publications as a subject of analysis. However, things have steered to relative stability over recent years, and data has been collected to a level now where longitudinal analysis of broader regional data has become more and more attainable.

Due to data limitations the analysis will not entail all (27) EU member states, but a panel data set will be constructed using data on the following 12 countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Spain, and Sweden for the 2005-2020 time period.

3.2. Research & Development

To measure research and development (R&D) output, private firm R&D spending data will be used at the country-aggregate level, as it is a direct measure of firm-level innovative efforts and often-used in literature (e.g., Francois & Lloyd-Ellis, 2003). Annual data on individual firm R&D expenditure, published by the Industrial Research and Innovation (IRI) department of the European commission is used. The datasets are published on a fiscal-year annual scale. The datasets are not all of similar length, as the top-500 was included for 2003 and the top-700 for 2004, after which the top-1000 was reported continuously. Since the inclusion on the datasets is not random, but based on a ranking method, the waves of 2003 and 2004 are excluded, as to prevent any positive average size-biases for these waves.

The company level data is (mean) aggregated to country level. The individual cross-sectional datasets are processed and merged into a balanced panel data set. Data on UK firms was initially included up until the last wave (2020, due to the Brexit), but had to be removed due to the exclusion of the UK in other datasets used in this study. UK firms were well represented in the earlier years (with a total of 4,452 observations over 17 waves).

The mean R&D spending (both country-level and aggregate) is calculated for each year and plotted with the (loess) mean in Appendix 3.3 to give us a general visual impression of the time trends in firm R&D spending. Due to their large magnitude, and the percentual nature of the other variables in the model, the logarithmic values of the R&D spending observations will be used hereafter. The country specific summary statistics can be found in appendix 3.1, with the aggregate sample summary statistics expressed below:

Variable	N	Mean	SD	Min	25%	75%	Max
R&D spending	192	4.775	0.718	2.718	4.252	5.36	6.041

Table 3.1: *Summary statistics for research and development (R&D) spending, expressed logarithmically*

3.3. Entrepreneurship

Annual data from the GEM (global entrepreneurship monitor) is used to quantify entrepreneurship at the country-level. The GEM Adult Population Survey (APS) measures the level and nature of entrepreneurial activity around the world. It is administered to a representative national sample of at least 2000 respondents. The data-collection started in 1999 in a few countries and has expanded a lot over the years as new national departments were founded, and the range of survey questions was expanded. The survey does suffer from missing observations, with some countries missing data for one or multiple reporting periods, this is likely due to a lack of data collection for that period. If one period was missing, with data reported for the period direct before and afterwards, the mean of the before and after periods was taken as the value for the missing period (7/196 cases). If data was missing for multiple consecutive periods, the observations were left blank, and not used in the quantitative analysis so as to prevent measurement error. This does mean that we are limited in data availability and variation and will have to resort to an unbalanced panel structure for our analysis.

Total early-stage Entrepreneurial Activity (TEA) and 'perceived opportunity' data is used for the time range of 2005-2020. TEA measures the percentage of the population (aged 18-64) who are either a nascent entrepreneur or owner-manager of a new business (<3.5 years old), for further detail see appendix 3.4 for the relevant survey coding scheme. The country-level summary statistics can be found in Appendix 3.1, with the overall sample summary statistic express in table 3.2 below:

Variable	N	Mean	SD	Min	25%	75%	Max
TEA	150	6.143	2.202	1.9	4.648	7.285	12.41

Table 3.2: *Summary statistics for total entrepreneurial activity (TEA) as a percentage of total pop.*

'Perceived opportunity' measures the percentage of the population (aged 18-64) who see good opportunities to start a firm in the area where they live, and will be used as a control variable, proxying for the 'systemic' (Stam, 2015) regional ecosystem effects commonly reported in entrepreneurial literature (e.g., Stuetzer et al., 2016, Leendertse et al., 2021, among others). See Appendix 3.9 for plots.

Variable	N	Mean	SD	Min	25%	75%	Max
PeOpp	160	39.957	15.518	13.9	28.275	48.877	81.56

Table 3.3: *Summary statistics for the perceived start-up opportunities (PeOpp).*

3.4. Economic cyclicality

As common practice in macro-economic literature (e.g., de Grauwe 2012), the output gap is used to measure the economy's cyclical movement along the business cycle. The data was collected from the OECD and is based on aggregates of national statistical offices and World bank data. The output gap is measured as the percentual deviation from potential output. The country-level summary statistics can be found in Appendix 3.2, with the overall sample summary statistic express in table 3.2 below:

Variable	N	Mean	SD	Min	25%	75%	Max
GAP	192	-1.182	3.346	-12.833	-2.425	0.843	8.322

Table 3.4: *Summary statistics for the output gap (GAP) as a percentage of potential GDP*

3.5. Animal spirits

In order to measure changes in differing confidence levels over time, Business and consumer survey data published by the European Commission is used. The European Commission created the Economic sentiment indicator (ESI), which is a composite measure (neutral = 100) of multiple sector specific confidence indicators. The ESI aims to combine judgements and attitudes of producers and consumers by means of a weighted aggregation of standardized input series. The individual sector indicators and their relative weight in the ESI are the Industrial confidence indicator (40%), Services Confidence indicator (30%), Consumer confidence indicator (20%), Retail trade confidence indicator (5%) and the Construction confidence indicator (5%). The above-mentioned weights are not directly applied to the five confidence indicators themselves but to their standardized individual component series.

The indicators are based on monthly surveys collected by each EU member state, under the *'Joint Harmonised EU Programme of Business and Consumer Surveys'.* The European commission services (DG ECFIN) is responsible for the production of aggregate survey results for the EU and the euro area on the basis of the results received from the Member States.

Sample weighing methods are applied at multiple levels by the DG ECFIN. Starting at the sub-sector level, based on short-term-statistics (STS) are used for the business survey. At the within country sectors level, weighing coefficients are constructed to 'reflect the relative significance of each stratum', often based upon statistics like the value added of a specific sector within the total national level industry in question. This weighing is applied by national statistical agencies to correct for any possible discrepancies of representation and is used to construct aggregate data on the national level. European aggregate replies to the questionnaires are calculated as weighted averages of the country aggregate replies. The weights are the shares of each of the Member States in an EU (euro-area) reference series and are smoothed by calculating a two-year moving average (see DG ECFIN, 2022 for further details).

Variable	N	Mean	SD	Min	25%	75%	Max
ESI	192	99.307	8.525	80.017	92.915	105.633	114.233

Table 3.5: *Summary statistics for the European Sentiment Indicator (ESI), with 100=Neutral sentiment*

The country specific summary statistics (Appendix 3.2) and trend plots (Appendix 3.8) can be found in the appendix of this study.

Methodology & analysis:

All the individually discussed datasets of chapter 3 were combined to create a detailed dataset which will be used to map trends over time and see whether different aspects can significantly explain observed variation ceteris paribus. This chapter will follow a stepwise procedure: (4.1.) first investigating the presence of unit-root and/or autoregressive tendencies in the individual series as well as cross-sectional dependence. (4.2.) Applying the findings of section 4.1 in order to investigate several theorized (partial) relationships in the overall dataset. (4.3.) Combining the findings of the previous sections, an overall model to test the research question will be formulated and tested accordingly.

4.1. Unit root, individual auto-regressive tendencies & cross-sectional dependence

4.1.1 Unit root

In order to test for the presence of unit-root in the variable observations, an augmented Dickey-Fuller (ADF) test is common practice for time-series analysis. In line with Im, Pesaran & Shin (2003), a unit-root test based on the average of (augmented) Dickey–Fuller statistics is for each group in the panel seems appropriate. Their proposed 'IPS' unit root-test allows for residual serial correlation and heterogeneity of the dynamics and error variances across groups in addition to the usage of unbalanced panel data sets. However, as it is part of what is considered the 'first generation unit-root tests' in literature, it does assume that no cross-sectional dependence (CD) is present. This assumption is rather strict for macro-economic panel datasets (see 4.1.3 for further detail), demeaning the panels per time unit reduces the potential impact of CD, and will hence be implemented, but slight effects might still be present (see limitations for further detail).

The number of lags to be included in unit-root tests affects the potential power and outcome of the tests and can thus be of importance. Academic literature has not yet settled on one decisive method to decide the number of lags to be added. Liew & Venus (2004) in their quantitative analysis of various methods find that the Hannan–Quinn information criterion (HPQ or HPiQ) is best at mathematically predicting the correct number of lags to be added for datasets (in particular for N>120, but it works well for lower N too). In line with this finding, the HPQ method was allowed to predict the number of lags to be used for each individual panel member in the following Im, Pesaran & Shin (IPS) unit root tests:

(1.) R&D, (IPS) unit root test was performed, and sufficient evidence was found to reject the notion of unit root in all panels (Wtbar = (-3.597) on an average of (1.50) lags, (p. <0.001)).
(2.) TEA, (IPS) unit root test was performed, and sufficient evidence was found to reject the notion of unit root in all panels (Wtbar = (-3.911) on an average of (1.25) lags, (p. <0.001)).
(3.) GAP, (IPS) unit root test was performed, and sufficient evidence was *not* found to reject the notion of unit root in all panels (Wtbar = (-0.297) on an average of (1.50) lags, (p. 0.383)).
(4.) PeOpp, (IPS) unit root test was performed, and sufficient evidence was found to reject the notion of unit root in all panels (Wtbar = (-5.555) on an average of (2.50) lags, (p. <0.001)).
(5.) ESI, (IPS) unit root test was performed, and sufficient evidence was found to reject the notion of unit root in all panels (Wtbar = (-3.732) on an average of (1.67) lags, (p. <0.001)).

The detailed test results can be found in Appendix 4.1. The results imply that we will hence assume GAP to be Integrated of order one (I (1)) and include it in first differences in our analysis.

Integration of order (2) is highly unlikely in macro-economic data, but still, an IPS unit root test was performed on GAP in first differences to ensure it's I (1) nature:

(6.) GAP', (IPS) unit root test was performed, and sufficient evidence was found to reject the notion of unit root in all panels (Wtbar = (-6.207) on an average of (1.58) lags, (p. <0.001)).

One should be careful interpreting the results of IPS unit root tests, as rejecting the null (unit-root in all panels) does not imply that the series is stationary in all panels, but rather for at least one panel member. Pesaran (2012) pleads for the identification of the exact proportion of the sample for which the null hypothesis is rejected, but this requires country-specific data sets with T sufficiently large, which is not the case. Hence for now, we will have to assume GAP to be I (1), and stationarity in the R&D, TEA, PeOpp and ESI variables tests (the limitations section contains a more detailed discussion surrounding unit-root tests).

4.1.2. Auto-regressive tendencies in the series

In order to visually examine whether we are dealing with auto-regressive tendencies in the variable series, the auto-correlation function (ACF) as well as partial ACF (PACF) were plotted for each variable that will be used as an independent variable in our analysis (see Appendix 4.2 – 4.4). The ACF was computed using the Durbin-Levinson algorithm and gives a first general idea of correlation with past values. The PACF shows the correlation of current with past values, while correcting for the correlation with other lags. The partial autocorrelations are obtained from Yule-Walker estimates of the successive auto regressive processes (as is common practice in AR literature) and will be used to make an estimation whether lags of the variables are likely to have a significant effect in explaining its current variation and should hence be included so as to prevent potential omitted variable biases. If the effect size is estimated to be (close to) 0.15 or smaller, they are seen as 'white noise', and will hence be excluded in future regressions.

As can be observed in Appendix 4.2 and 4.3, both TEA (lag (1) ≈0.78, and lag (2) ≈0.22) and R&D (lag (1) ≈0.88) show positive PACF correlation numbers which are larger than the set boundaries for 'noise'. The ACF graphs all seem to suggest a geometrically declining series, in line with expectations. These findings are not unexpected, as R&D investments are a long run investment type, and TEA measures start-up activity over the past 3.5 years. Hence, in line with the PACF findings, TEA will have lags (2) included and R&D lags (1) in future regressions. The inclusion of these lagged dependent values can help to reduce the potential presence of serial correlation, and thus help to further validate future regression results. As GAP was found to be I (1) (see section 4.1.1) and is expressed in first differences now, we find no serious signs of autocorrelation when computing it's PACF (see Appendix 4.4), as is to be expected.

4.1.3. Cross-sectional dependence

Recent econometric literature has started to question econometric assumptions surrounding the validity of estimates under heterogeneous and potentially cross-sectional dependent panel data. The inconsistency of pooled estimators in dynamic heterogeneous panel models has been demonstrated by Pesaran and Smith (1995), and Pesaran et al. (1996). In line with Driscoll and Kraay's (1998) original finding for small balanced panels, Monte Carlo experiments by Hoechle (2007) reveal that erroneously ignoring spatial correlation in panel regressions commonly leads to overly optimistic (anticonservative) standard error estimates, irrespective of whether a panel is balanced or not. Such cross-sectional dependence (CD) can lead to bias in tests results (also called contemporaneous correlation). Time series for different cross-section units can be correlated, as a result either from unobserved factors, or from spatial or spillover effects.

Although Driscoll and Kraay (1998) standard errors tend also to be slightly optimistic, their small-sample properties are considerably better than those of the alternative covariance estimators when cross-sectional dependence is present. Driscoll & Kraay standard errors are heteroskedasticity- and autocorrelation-consistent and robust to general forms of spatial and temporal dependence. Due to the likely inter-dependence of the individual European economies studied, because of their strong inter-regional trade dependency, cooperation (through e.g., the EU/European institutions) as well as geographical proximity, cross-sectional dependence will be assumed to be present. This assumption introduces new difficulties in testing for autocorrelation in the regression errors, hence we will have to assume these to be present out of caution and require a method of controlling for their presence. Luckily, Driscoll and Kraay standard errors correct for this too. To conclude: in order to account for the (potential) existence of cross-sectional dependence, heteroskedasticity as well as autocorrelation in our data, Driscoll and Kraay robust standard errors will be used in the following regressions.

4.2. Partial Relationships

Now that we've studied the individual series' behavior over time, we will continue in this section by exploring if the theorized relationships exist. All tests will be performed at the standard 95% confidence interval (p. 0.05), unless specifically stated otherwise. The stepwise research question model as introduced by figure 1.1 in the introduction will be followed.

We use fixed effects (FE) estimators since we're dealing with macroaggregated data at the country level in a constant sample of the same countries. Due to this fact, we cannot treat our sample as a random sample from a large population (as would implied in using a Random-effects type of model). FE is mechanically the same as allowing a different intercept for each cross-sectional unit, which can help capture country-specific unobserved effects that might affect the regression results (Wooldridge, 2015). FE estimation is consistent whenever the unobserved effects are either fixed or random (Hausman 1978), which we assume to be the case here, since we assume them to stem from country specific historical characteristics, or random processes.

It is common to find time-dependent trends in (macro)-economic data (Wooldridge 2015), to account for the potential presence of such trends, a linear time trend (Year) will be added to the regression models.

Since we're dealing with country level data with one or multiple years of data missing for certain countries (see Appendix 3.6 for a graphical representation), we're dealing with unbalanced panel data. Hence, we must assume that the reason some observations are missing is not systematically related to the idiosyncratic errors (Wooldridge, 2015), as no concerning patterns seem to emerge from the plots in Appendix (3.3, 3.6 - 3.9), we assume this to hold for now.

4.2.1 The effect of the output gap on entrepreneurship

In accordance figure 1.1 of the introduction, we'll start by studying the first half of part (a.) of the research question: *'what is the effect of the business cycle on private innovation through the channel of Entrepreneurship'*, as visually expressed in figure 4.1:

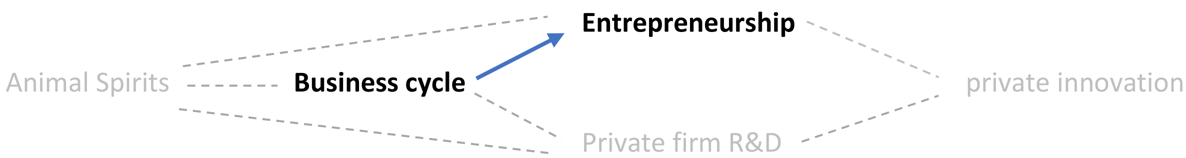

Figure 4.1: *The relationship currently being explored*

The effect of business cycle movements on total entrepreneurial activity (*TEA*) might not be instant, but there could be a lagged effect present, hence lags of the annual percentual EU GDP growth statistics (*GDP*) will be added. Since the TEA variable reports on start-ups started in the past 3.5 years, lags of GAP to order (3) will be added to the model to account for the total effect the output gap could have potentially had on current start-up activity.

Since entrepreneurship research reports a high influence of regional 'systemic' (or contextual) factors (see e.g., Stam, 2015, Stuetzer et al., 2016, Leendertse et al., 2021), perceived opportunity (*PeOPP)* and its lags (2) will be added as a control variable to proxy for such effects. Combined, these elements form the initial dynamic panel model to be tested:

$$(4.1.)\quad TEA_t = \alpha_0 + \sum_{j=1}^{2} \beta_i TEA_{t-j} + \sum_{j=0}^{3} \beta_i GAP'_{t-j} + \sum_{j=0}^{2} \beta_i PeOpp_{t-j} + Year_t + v_t$$

Expression 4.1.

Where (*t*) represents the time period (year), (*i*) the individual country id and (*v*) the error term.

Driscoll & Kraay standard errors were applied, and overall significance of the model was found (F. 119.48, p.<0.001, Within R-sq 0.377). Interestingly, significant individual effects were found for the first lag of GAP' (p.0.002). The second lag of GAP' (p. 0.058) is significant at the 10% level. All other variables were found to be individually insignificant ceteris paribus (see Appendix 4.5, column 4.1. ('TEA.1') for the full regression results).

The results suggest a delayed, but significant effect of output gap on total entrepreneurial activity ceteris paribus, in line with what was expected based upon the literature. This result means that significant quantitative evidence has been found that the relationship visualized by the blue arrow in figure 4.1. does indeed exist for our sample, i.e., the fluctuations along the business cycle can significantly affect entrepreneurial start-up activity. This finding can be used as a first building block for our main model specification in section 4.3.

4.2.2 The effect of the output gap on private firm R&D spending

Secondly, we'll explore the potential relationship between fluctuations in annual output gap and firm R&D spending. As mentioned in the data section, R&D growth (expressed in (€) millions) will be expressed logarithmically in order to maintain linearity in the model.

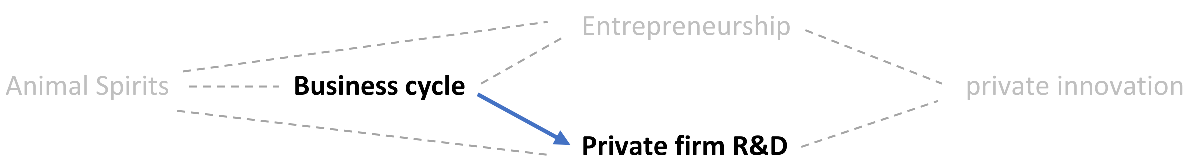

Figure 4.2: *The relationship currently being explored*

Similar to total entrepreneurial activity, R&D spending is theorized to be affected by current output gap levels as well as output gap levels in previous years (lags). Lags of output gap likely affect current R&D spending since research and development is a long time-horizon process both in terms of outcomes as well as investments made.

In line with what is common practice for annualized macro-economic data, lags of order (2) will be added to the model in order to capture such potential effects on current and last-years R&D spending. The model thus shows quite some similarities to expression 4.1:

$$(4.2.)\quad Log(R\&D)_{it} = \alpha_0 + \beta_i Log(R\&D)_{it-1} + \sum_{j=0}^{2} \beta_i GAP'_{t-j} + Year_t + u_t$$

Expression 4.2.

Where (*t*) represents the time period (year), (*i*) the individual country id and (*v*) the error term.

Driscoll & Kraay standard errors were applied, and overall significance of the model was found (F. 112.27, p.<0.001, Within R-sq 0.729). With significant individual effects found for GAP' (p. 0.010) and the lag (1) of R&D spending (p.<0.001) itself. The first lag (p. 0.800) and second lag of GAP' (p. 0.305) were not significant at both the 5% and 10% level. All other variables were found to be individually insignificant ceteris paribus (see Appendix 4.5, column 4.2. ('R&D.1') for the full regression results).

The results suggest a significant effect of current output gap variation on firm R&D spending ceteris paribus, as well as a substantial autoregressive tendency in the series. Such results are not unexpected, as R&D investments have a long time-horizon and involve a high level of sunk costs (see e.g., Francis & Lloyd, 2003). Such findings suggest a certain type of 'stickiness' to R&D investments, where perhaps part of its level fluctuates with the company's profit-level changes along the business cycle (see discussion & implications for further detail).

The significant effect of GAP' on R&D spending found in this model does mean that the relationship hypothesized in figure 4.2 holds, a finding which will come back in our main model specification in section 4.3.

4.2.3. The effect of economic sentiments (animal spirits) on the output gap

Next, we'll examine whether the suggested relationship between animal spirits, quantified by the European Sentiment index (ESI), and the Business cycle, quantified by fluctuations output gap over time holds for our sample. This potential relationship will form the basis for our attempt to answer part (b.) of the research question: '*is this effect [of the business cycle on private innovation] altered by animal spirits affecting the business cycle?*'.

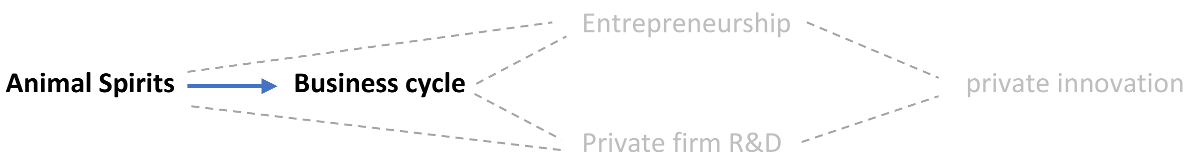

Figure 4.3: *The relationship currently being explored*

To allow animal spirits (ESI) to have a delayed effect on GAP' too, lags of order (3) were added to the model, as summarized in expression 4.3:

$$(4.3.)\ \ GAP'_{it} = \alpha_0 + \sum_{j=0}^{3} \beta_i ESI_{t-j} + Year_t + u_t$$

Expression 4.3.

Where (t) represents the time period (year), (i) the individual country id and (v) the error term

Driscoll & Kraay standard errors were applied, and overall significance of the model was found (F. 72.260, p.<0.001, Within R-sq 0.608). With significant individual effects found for ESI (p.<0.001) and the lag (3) of ESI (p. 0.046). The linear time trend included in the model was also found to be significant (p. 0.017). All other variables were found to be individually insignificant ceteris paribus (see Appendix 4.5, column 4.3. ('GAP'') for the full regression results).

These results suggest a significant effect of European sentiment index (ESI) variation on output gap, both in the current period and with a delayed effect (lag 3), ceteris paribus. Such a delayed effect is a rather interesting finding and could be seen as a sign of a long-term interrelatedness of fluctuations in economic sentiment and cyclical movements of the output gap along the business cycle.

Such findings are in line with the previously discussed work of De Grauwe (2012) and Farmer & Guo (1994) and form the final part of our partial relationship models. The regression results of expression 4.1. – 4.3. suggest that the relationship hypothesized in part (a.) of the research question (*What is the effect of animal spirits on private firm R&D and Entrepreneurship through the business cycle?* Is likely present, and of significant size, since ESI significantly explains variation in GAP, which (combined with it's lagged values) in turn was found to be of significant explanatory for TEA and R&D. These findings are in line with the literature previously discussed in this study and will form the basis for our main model specification following hereafter.

4.3. Main model

After all these individual effects have been studied, it is time to quantitatively explore stage 2 of the research question: (b.) *Do animal spirits affect private innovation directly, controlling for the effect through the business cycle?* Where we return to the model as expressed in figure 1.1 of the introduction:

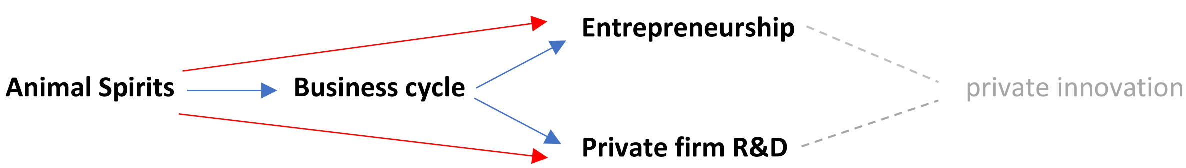

Figure 4.4: *The relationship currently being explored, with stage 1 (section 4.2) in blue and stage 2 in red.*

Expressions (4.1 to 4.3) will be combined to come to the combined model for testing the research question of this study. Interaction terms of (*GAP*ESI*) were added in both the current time period as well as a lag of order (2) in order to capture the effect of animal spirits on (as found in section 4.2.3) and through the business cycle. In order to still give the non-interaction terms containing GAP and ESI meaning, the mean (μ) of each panel member's observation series was subtracted in the interaction term. Now the individual variable results of ESI and GAP can be read as the partial effect on the dependent variable at mean value of the other (rather than 0, which doesn't make sense for e.g., ESI (neutral = 100, min. = 80.01)).

All of this is combined with the findings of sections 4.1 and 4.2 into the following main model expression for total entrepreneurial activity (TEA) (4.4.):

$$(4.4)\quad TEA_t = \alpha_0 + \sum_{j=1}^{2} \beta_i TEA_{t-j} + \sum_{j=0}^{3} \beta_i ESI_{t-j} + \sum_{j=0}^{3} \beta_i GAP_{t-j} + \sum_{j=0}^{2} \beta_i PeOpp_{t-j}$$

$$+ \sum_{j=0}^{2} \beta_i (GAP'_{t-j} - \mu GAP_i)(ESI_{t-j} - \mu ESI_i) + Year_t + u_t$$

Expression 4.4.

Where (for both 4.4 and 4.5) (*t*) represents the time period (year), (*i*) the individual country id and (*u*) and (*v*) the error terms.

Driscoll & Kraay standard errors were applied, and overall significance of the model was found (F. 58.33, p.<0.001, Within R-sq 0.431). The full regression table can be found in Appendix 4.5, column 4.4. ('TEA.2'), we will discuss the significant individual findings in the following paragraphs:

Whereas the first lag of TEA (p. 0.195) could not significantly explain variation in TEA itself ceteris paribus, significant effects were found for the second lag of TEA at the 10% level (p. 0.077), confirming the earlier findings of expression 4.1. with regards to the lagged values of TEA.

In line with the findings of expression 4.2, the first lag (1) of GAP was found significant (p.<0.001), the second lag (2) of GAP was found to be significant (p. 0.003) at the 5% level too now (this was only at the 10% level in expression 4.2). Confirming a strong relationship between TEA and past output gap levels.

The control variable of PeOpp (perceived opportunity) was found to be insignificant at the 5% level, but significant at the 10% level, a finding which can be seen as support for the notion of 'systemic contextual factors' affecting entrepreneurial activity.

The interaction term of GAP and ESI was found to be a significant individual explanatory variable for predicting entrepreneurial output (TEA), (p. 0.039). This finding giving us quantitative evidence for an effect of animal spirits through the business cycle on entrepreneurial activity at mean output gap values, in line with our hypothesis.

Part (b.) of our research question theorizes a potential relationship between animal spirits (measured by ESI) and the channel(s) of entrepreneurship (and R&D). For this, ESI should significantly explain variation in TEA on a country level ceteris paribus, such a result was found (p. 0.030) for the current level of ESI.

In similar fashion to the procedure of expression 4.4. (for TEA), the demeaned interaction terms of ESI*GAP and findings of section 4.1 and 4.2 lead to the main model expression for R&D spending (4.5.):

$$(4.5.)\quad Log(R\&D)_{it} = \alpha_0 + \delta_i Log(R\&D)_{it-1} + \sum_{j=0}^{3} \delta_i ESI_{t-j} + \sum_{j=0}^{2} \delta_i GAP'_{t-j}$$

$$+ \sum_{j=0}^{2} \delta_i (GAP'_{t-j} - \mu GAP_i)(ESI_{t-j} - \mu ESI_i) + Year_t + v_t$$

Expression 4.5.

Where (for both 4.4 and 4.5) (*t*) represents the time period (year), (*i*) the individual country id and (*u*) and (*v*) the error terms.

Driscoll & Kraay standard errors were applied, and overall significance of the model was found (F. 427.47, p.<0.001, Within R-sq 0.746). The full regression table can be found in Appendix 4.5, column 4.5. ('R&D.2'), we will discuss the significant individual findings below.

In line with the findings of expression 4.2., The current output gap (GAP') was found to be significant (p. 0.003). Thus, confirming the earlier findings of output gap affecting R&D spending levels. The lagged value of R&D spending was found to significantly explain variation in current R&D spending (p.<0.001) again too.

With regards to our main research question (b.), contrary to the findings for TEA, no significant effect of the interaction term on R&D spending was found. Apart from the lag (3) values of ESI (p.0.064), no significant effects of ESI in predicting R&D values could be found at either the 5% or the 10% level.

One should bear in mind that, although we control for a range of dynamic and observable characteristics, unobserved time-varying variables that are not independent of the dependent variable and independent variables could still lead to inconsistent estimators. We'll further dive into this notion in the following robustness section of this study.

Robustness

Since fixed effects were applied on models containing lagged dependent variables, we run the risk of the lagged dependent variable being correlated with the error term in the fixed effects specification of our dynamic panel model. Such a bias is known as the 'Nickell bias' (see Nickell, 1981) and diminishes with increasing T (time periods) in a study. As our time horizon (16) is rather short, this study may suffer from such problems of endogeneity.

As suggested by Hsiao (2007), a generalized method of moments estimator (GMM) can help overcome the endogeneity introduced by the potential presence of Nickell biases. The GMM estimator has the advantage that it is consistent and asymptotically normally distributed whether unobserved effects (αi) are treated as fixed or random because it eliminates (αi) from the specification. However, the number of moment conditions increases at the order of (T^2) which can create severe downward bias in a finite sample (Ziliak, 1997). A GMM approach also assumes that no-serial correlation or heteroskedasticity between individuals is present in the idiosyncratic error terms, something which proved difficult to test for under the assumed presence of cross-sectional dependence (see 4.1.3). The standard errors will be made robust and clustered on a country-level, but the following results should thus still be read with some caution.

An Arellano and Bond (1991) GMM estimation model allows for heteroskedasticity and autocorrelation within individual units' errors and uses fixed individual effects (implying unobserved heterogeneity). In order to see if the results differ when controlling for the potential presence of Nickel and omitted variable biases in our datasets an Arellano and Bond GMM model was used to re-run the dynamic panel regression models (4.1. – 4.5.). The full regression results can be found in Appendix (5.1.), we'll discuss the significant differences between the FE with Driscoll and Kraay robust standard errors regressions of chapter 4 and the Arellano and Bond GMM estimations for each model below:

Model 4.1. (TEA over GAP and PeOpp): overall still significant (Wald chi = 124.30, p.<0.001)
Differences: GAP' lag(2) loses it's 10% significance (p.0.185 now)

Model 4.2. (R&D over GAP):): overall still significant (Wald chi = 466.65, p.<0.001)
Differences: no differences in individual significance of variables at either 5% or 10% sig. levels

Model 4.3. (GAP over ESI): overall still significant (Wald chi = 464.76, p.<0.001)
Differences: The nature of the GMM model (lagged dependent variables) introduces lag (1) of GAP' to the equation, which is found to be highly significant (p<0.001). The lag(2) of ESI becomes sig. (p. 0.024), where this was insignificant in the FE model (p. 0.339).

Model 4.4. (Main model for TEA): overall still significant (Wald chi = 79.72, p.<0.001)
Differences: ESI turns highly insignificant (p.0.776) vs. (p.0.030) in the FE model.

Model 4.5. (Main model for R&D): overall still significant (Wald chi = 11975.65, p.<0.001)
Differences: Interestingly, whereas it was found to be insignificant in the FE model, ESI turns highly significant (p.<0.001) as well as it's lag (3) value (p. 0.018). The demeaned interaction term of GAP*ESI turns significant too (p. 0.019).

Thus, the majority of the relationships found in the FE model seems to hold in the GMM model too. The main notable difference is the switch from TEA to R&D showing significant results for our hypothesis.

Discussion & Implications

The main FE-Driscoll Kraay and the Arellano-Bond GMM model offer differing results with regards to the effect of economic sentiment values on the individual sources of private innovation (firm R&D and entrepreneurship). In an aggregate sense however, both models can be seen as providing evidence that economic sentiments affect private innovation initiatives in both an indirect (through their effect on the business cycle) as well as a direct way. The found effects where not only temporal, but past (lagged) values were found to significantly affect current innovative efforts in a direct way too.

The study of intertemporal confidence indicators and confidence swings is actually common practice in the fields of finance, where they are reflected in the famous notions of a 'bull' (= optimistic, expanding), or 'bear' market (= pessimistic, retreating). The findings of this study suggest that such notions are likely affecting innovative efforts too and should receive more attention in future (policy) considerations.

The output gap itself was found to significantly affect private market innovative efforts too, with even it's past value sometimes helping to significantly explain variation such efforts now in the case of entrepreneurship (although this might be due to the multi-year (3.5) measurement characteristic of the TEA value). Both firm R&D and entrepreneurship where however found to be affected by the current stance of the output gap, thus suggesting a further role for business-cycle considerations in innovation targeting policy efforts.

Combined, our findings suggest that business-cycle movements as well as economic sentiment indicators should receive more consideration in the formulation process of successful innovation targeting policies. As an aggregate, they could help predict volatility and uncertainty in the market conditions faced by the innovating parties. Better understanding of such conditions can be of importance, as technologically successful new products might not be adopted in markets facing high levels of uncertainty (Eggers, 2012; Hellmann and Perotti, 2011).

This notion is relevant, since (private market) innovation is seen as one of the key tools in acquiring or maintaining a competitive advantage as an economy (Cohen & Klepper, 1996b.) In accordance with this, governments spend substantial amounts of tax-payer money on e.g., tax-benefits, subsidies, and other investment efforts in an attempt to promote domestic innovative efforts. Literature has shown that such investments are highly likely to suffer from questionable effectiveness and efficiency whenever the responsible institutions lack expertise to understand the (specific) market conditions (see e.g., Wolff & Reinthaler, 2008; Choi & Lee, 2017; Audretsch, 2020). In line with such findings, we believe that the results of our study show that a better understanding of economic sentiments and business cycle movements can help (governmental) institutions improve their subsidy and innovation-targeting efficiency. The findings of Audretsch et al., 2020 in particular could help form a basis for the development of a more targeted and effective set of innovation policies.

Due to the exploratory outset of this study, more research is definitely desirable in order to further our understanding of the interrelationships between business cycle movements, economic sentiments, and private innovative efforts. We have to acknowledge that this study and its methodology does come with its shortcomings (see limitations), but our findings have not been found in previous literature, and hence can be seen as a valuable contribution to our current understanding of innovative efforts and their (potentially far-reaching) relationship with economic phenomena.

Limitations & suggestions for future research

Due to limitations in data availability, we had to use annual data over a relative short-time span. Together with the fact that only 12 EU members had enough reported data observations to justify inclusion into our panel, this leaves us with limited volatility for quantitative analysis. The necessity of an unbalanced panel structure brought further limits and challenges to the quantitative methodology and conclusions. Sub-annual data, or data spanning a longer (and preferably continuous) timeframe would have allowed for more robust regression conclusions. Such types of data could be implemented in future research (e.g., by using quarterly (rather than annual) firm reports for R&D spending figures and/or different measures of entrepreneurship as more data sources and types become feasible for longitudinal quantitative analysis). The introduction of more control variables and macro(-economic) trends (e.g., inflation and inflationary sentiment responses, technological advancement and digitalization or taxation) could help to further solidify our understanding of the phenomena at play.

Despite demeaning in the IPS unit-root procedure, cross-sectional dependence might still somewhat affect its results. Future research could implement so-called ‘second generation unit root tests’ , which account for the presence of cross-sectional dependence. Pesaran (2007) developed what is known as the Pesaran CADF unit-root test. In line with the IPS unit-root test (as implemented in this study), it is based on the mean of individual DF (or ADF) t-statistics of each unit in the panel. The null hypothesis assumes that all series in the panel are non-stationary (i.e., unit-root). To eliminate the potential presence of cross-sectional dependence, the standard DF (or ADF) regressions are augmented with the cross-section averages of lagged levels and first differences of the individual series. It does however come with its limitations surrounding the usage of unbalanced datasets, which proved it to be unviable for inclusion in this study (note: Pesaran (2007) does suggest a potential way to circumvent such issues, but these were (as of yet) not implemented in the statistical software packages used for this study).

Although this study focused on innovation initiated by private market agents, they are not the sole source of innovation. Public institutions as well as public-private partnerships (through e.g., university spin-offs) play a major role in innovation creation too (see e.g., Garsney & Heffernan, 2005; Theodoraki, 2018). Although the study’s aim was to exclude this branch of innovation from the realm of study, the public and private realm are often intertwined in the real world when it comes to innovation creation. University publications, education, and partnerships might result in start-ups, spin-offs, or collaborative research efforts with private entities. Additionally, innovation and research subsidies are common practice by various governments – where the idea is that they invest in (maintaining) a competitive advantage for their domestic firms and knowledge centers (the potential impact of such subsidies has its own branch of study, see e.g., Barlevy, 2007; Shane, 2009). Since the presence and size of such effects was not reported in the used datasets, they could not be controlled for, and are likely (somewhat) present in the reported outcomes of R&D and entrepreneurship. True disentanglement of private and publicly funded and performed innovation can thus not be guaranteed (although that might be an arbitrary distinction anyway). Suggestions for future research surrounding these matters are: (1.) Exploring and making an attempt at quantifying the effect size of public-private innovation cooperation (2.) Introducing public institutions as a third source of innovation, and testing whether the hypothesized relationships and results of this study hold for the public realm too, or whether different effects can be found and/or theorized for that specific branch of innovation.

Despite the fact that the output-gap has become the academic standard for modelling the business-cycle, it does not come without controversy either. As discussed in section 2.4 of the literature review, the main criticism surrounds the fact that 'potential output' can only be calculated ex-ante and is conditional to a variety of (potentially artificial) assumptions. Such assumptions may not necessarily reflect real-world conditions and run the risk of selection-biases through their construction and arbitrage for inclusion based upon theoretical models and institutional selection procedures. Future research could make an attempt at disentangling the output gap assumptions in further detail and see how and if different assumptions and models might impact both business-cycle modeling as well as animal spirits literature.

In this study a more extensive sentiment index was included, to allow for a wider range of sentimental fluctuations and capture a broader realm of the economy. Common practice in most animal spirits literature up to date however is to solely rely on consumer-sentiment indexes as a quantitative measurement of the animal spirits' concept. Almost all publications regarding animal spirits focus on the U.S., and hence the Michigan Consumer Sentiment index is a widely used data source in the literature. Further analysis of the various sentiment indexes and their relative strengths in capturing the phenomena related to the concept of animal spirits could be an interesting basis to help advance our understanding.

The academic field of entrepreneurship has seen a lot of development over the recent years. Ever since the publication of Stam and co-authors (Stam, 2015; Stam et al., 2017) influential pieces on the 'Entrepreneurial Ecosystem', the literature has come to a consensus that the ('systemic') context has a strong conditional power over the chance of both the birth and success rate of new entrepreneurial ventures. We aimed to capture such effects in a broad sense by the usage of the 'perceived opportunity' variable of the GEM survey. However, a random representative sample of a country's adult population might not form the ideal panel of judgement for entrepreneurial context, perhaps survey data among entrepreneurs or some other measure of entrepreneurial context would be more accurate in future research.

A limitation of the current measure for entrepreneurship (TEA), is that it does not entail any information on the innovativeness of the ventures. The GEM survey did offer questions regarding the innovative efforts of the new ventures it reports on, but inclusion of this variable would've meant too large of a data loss timewise (as the variable was only introduced to the survey in the more recent waves). Future research could make a further attempt at capturing innovative entrepreneurship through the inclusion of different measurements and conditions for innovative entrepreneurial output (see e.g., Audretsch et al, 2020). Or perhaps focus on a potentially beneficiary impact of (innovative) entrepreneurship on broader societal challenges (see e.g., Bischoff et al., 2017; Tiba et al., 2021), and the interrelations there.

A final suggestion for future research would be to investigate the impact of firm R&D and entrepreneurship on innovation in terms of (investment) efficiency and what a healthy balance of both should entail. Literature currently seems mixed on the matter, with some suggesting large firms crowd out smaller, often more innovative firms (e.g., Stuetzer 2016), and others (e.g., Cohen & Keppler, 1996a) suggesting a cost-spreading benefit of large firms, allowing for a higher level of innovative efforts. New insights could help a (regional) government to increase policy effectiveness and help to promote and potentially steer private innovative efforts towards 'desirable' outcomes (see e.g., Choi & Lee 2017 for further conditions and discussion).

Conclusion

This study has implemented both a Fixed effects model with Driscoll Kraay standard errors as well as an Arellano-Bond GMM model in an attempt to quantitatively analyze whether animal spirits affect private innovative efforts. The research question hypothesizes both an indirect (through their effect on the business cycle), as well as a direct effect of animal spirits on private innovative efforts. Despite mixed results between both models with regards to the effects on the individual sources of private market innovation (entrepreneurship and firm R&D), both models confirmed the presence of the theorized relationships in the aggregate.

Literature suggests that governmental institutions currently lack a proper understanding of the (market) conditions surrounding innovative efforts. The findings of this study could thus help to further our understanding of private market innovation and help increase governmental policy efficiency.

All-in-all this study should be seen as an explorative attempt to combine and quantify novel theorized macro-economic relationships using real-world datasets. We theorized and tested a new direct relationship between economic sentiments and private innovation sources and found individually mixed, but significant overall results. Naturally such a process comes with its drawbacks and limitations, but we do hope to have lit a spark of inspiration for further thorough research and analysis.

As science progresses, and more findings and data become available, new insights and advancements in the various fields involved in this study may help to improve and/or alter the findings presented here today. New and improved ways of measuring the concepts surrounding innovation and animal spirits can bring further clarity and depth to the phenomena and their interrelatedness.

As human beings, the understanding and modelling of our own behavior remains an ever-evolving cycle of creating, testing, confirming, and breaking with (scientific) paradigms and theories (see e.g., De Regt et al., 2007; Barber, 2009). In line with such notions, and all the phenomena analyzed discussed in this study, we can be nothing but excited for what the future may bring.

Personal note from the author: *To quote one of my favorite movies: "buy the ticket, take the ride" (Fear and Loathing: Las Vegas), and what a ride I've gotten myself on to with this thesis. I set out on an explorative adventure through all fields covered in my academic career, and found new knowledge, perspectives, and interesting relationships between various factors at play in our (macro-) world today. It has been a challenging deep dive along various realms and edges of academia, but I can honestly say that I tried my best and I am proud of the work in front of you today. How frustrating and scary the process may have sometimes been, I am more than delighted to say and acknowledge that I 'bought the ticket and took the ride', and I hope to have offered you, the reader, a glimpse of that feeling too. –* ***M.***

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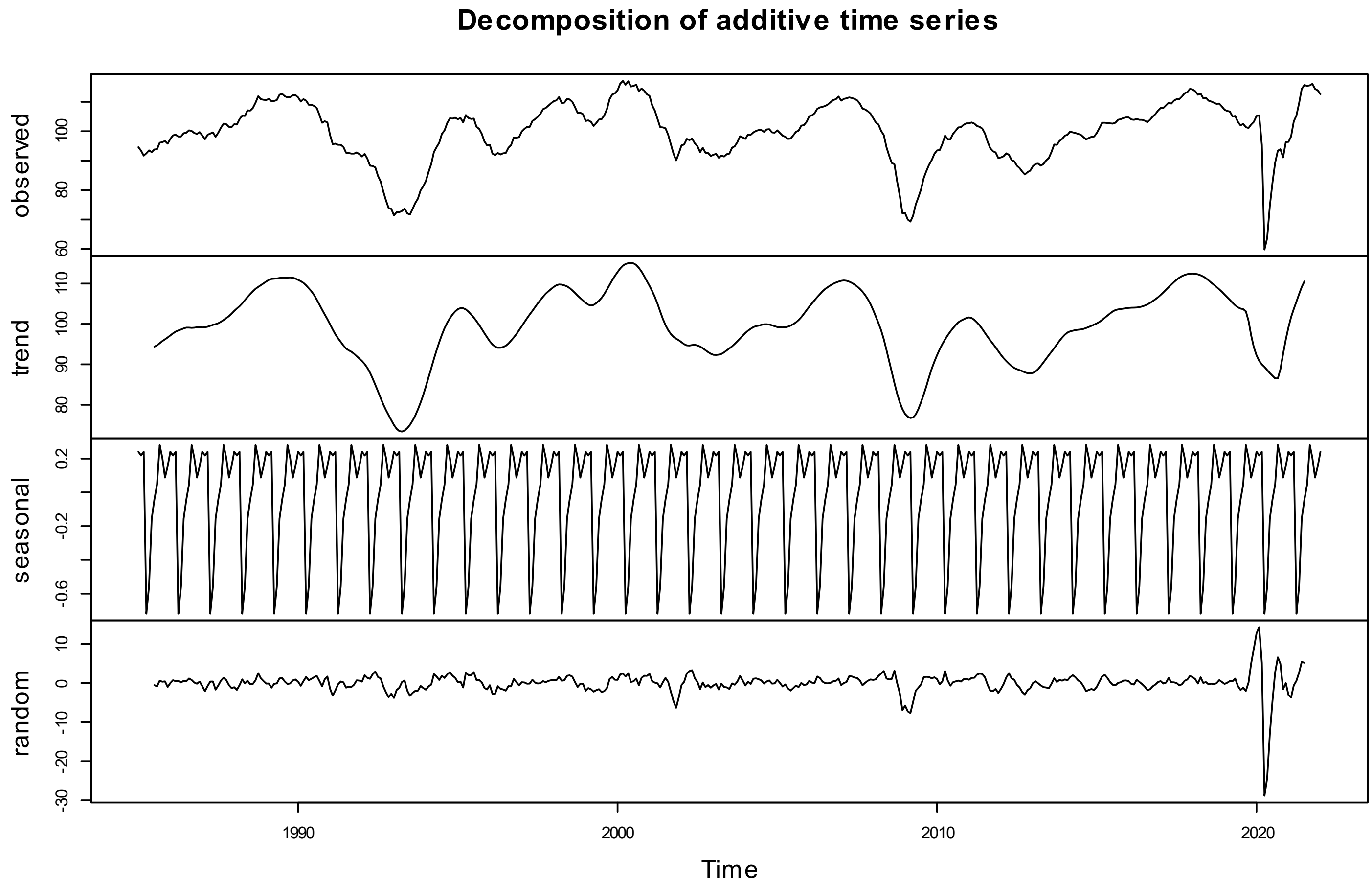
Appendix



Appendix 2.1: *trends of monthly ESI observations (1985-2022), showing additive seasonality (≈ 1.1).*

Summary statistics by country

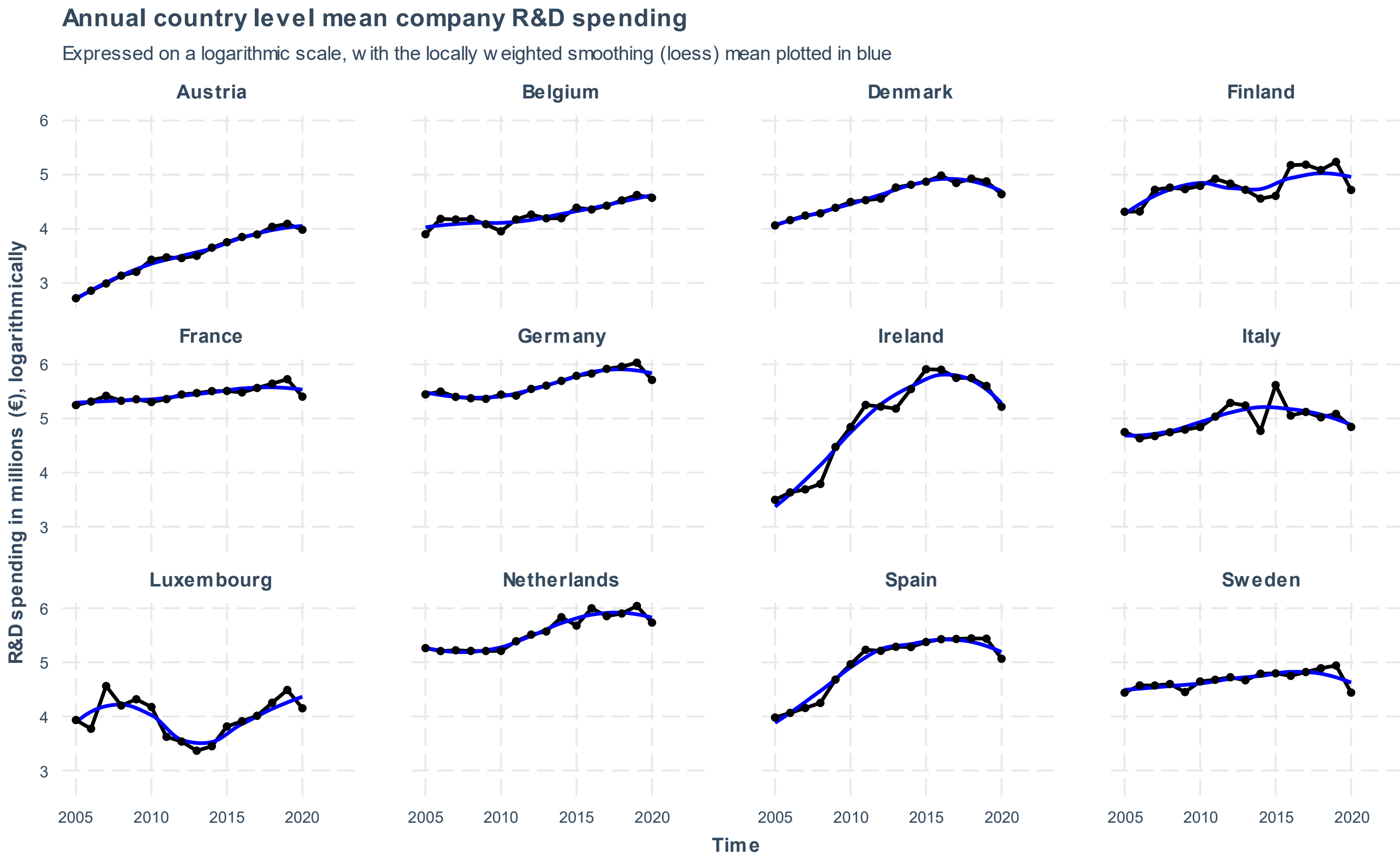
Variable	N	Mean	SD	Min	25%	75%	Max	Variable	N	Mean	SD	Min	25%	75%	Max
Country: Austria															
TEA	7	7.534	3.003	2.44	5.74	9.605	10.9	R&D spending	16	3.502	0.428	2.718	3.188	3.861	4.092
Country: Belgium															
TEA	11	4.299	1.231	2.73	3.33	5.3	6.24	R&D spending	16	4.263	0.207	3.901	4.173	4.4	4.625
Country: Denmark															
TEA	9	4.702	0.734	3.64	4.04	5.36	5.47	R&D spending	16	4.591	0.295	4.064	4.364	4.853	4.985
Country: Finland															
TEA	12	5.958	0.804	4.92	5.26	6.62	7.34	R&D spending	16	4.794	0.278	4.316	4.691	4.965	5.237
Country: France															
TEA	13	4.993	0.855	3.17	4.39	5.64	6.13	R&D spending	16	5.442	0.129	5.248	5.348	5.507	5.726
Country: Germany															
TEA	15	4.966	0.907	3.77	4.385	5.275	7.63	R&D spending	16	5.627	0.224	5.364	5.437	5.799	6.032
Country: Ireland															
TEA	14	8.58	1.789	6.15	7.275	9.562	12.41	R&D spending	16	4.954	0.863	3.498	4.303	5.639	5.909
Country: Italy															
TEA	15	3.915	0.956	1.9	3.45	4.52	5.01	R&D spending	16	4.97	0.264	4.634	4.766	5.094	5.618
Country: Luxembourg															
TEA	8	9.147	1.209	7.14	8.518	10.192	10.72	R&D spending	16	3.973	0.362	3.367	3.735	4.214	4.562
Country: Netherlands															
TEA	16	8.38	2.499	4.34	6.742	10.328	12.29	R&D spending	16	5.552	0.313	5.208	5.219	5.838	6.041
Country: Spain															
TEA	16	5.877	0.872	4.31	5.225	6.24	7.62	R&D spending	16	4.955	0.543	3.98	4.573	5.387	5.442
Country: Sweden															
TEA	14	6.294	1.582	3.45	5.11	7.297	8.25	R&D spending	16	4.673	0.155	4.44	4.572	4.791	4.941

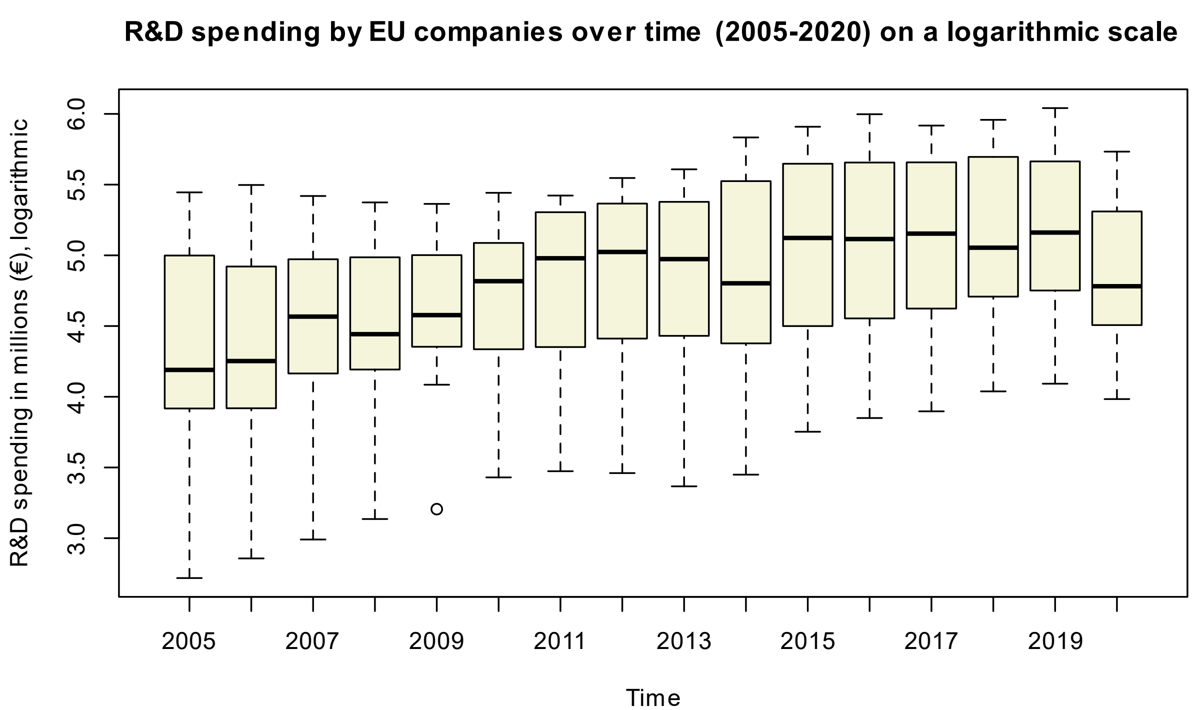
Appendix 3.1: *Summary statistics for TEA and R&D spending on a country level (2005-2020).*

Summary statistics by country

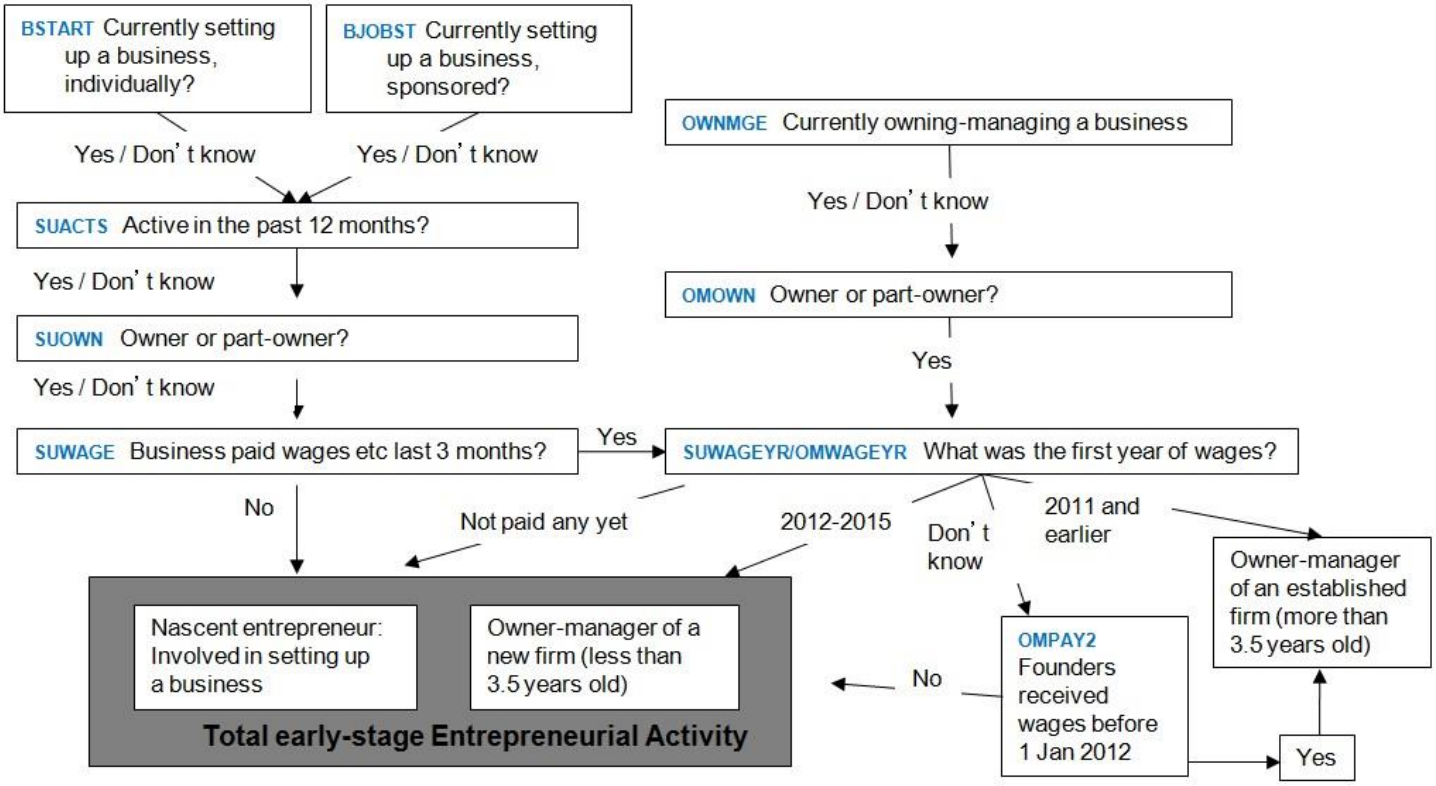
Variable	N	Mean	SD	Min	25%	75%	Max	Variable	N	Mean	SD	Min	25%	75%	Max
Country: Austria															
GAP	16	-0.901	2.421	-7.317	-2.04	0.949	2.706	ESI	16	99.496	9.06	80.017	95.556	105.16	112.992
Country: Belgium															
GAP	16	-0.664	2.16	-6.776	-1.382	0.383	3.156	ESI	16	99.033	8.411	80.392	94.558	103.079	111.867
Country: Denmark															
GAP	16	-0.563	2.401	-3.942	-2.425	0.726	3.988	ESI	16	99.92	8.889	82.958	94.948	106.71	113.625
Country: Finland															
GAP	16	-1.047	3.459	-5.087	-3.654	0.334	6.323	ESI	16	98.681	9.456	83.05	91.267	107.4	112.233
Country: France															
GAP	16	-0.715	2.577	-8.38	-1.523	0.722	3.097	ESI	16	97.814	8.157	81.925	90.933	103.21	110.708
Country: Germany															
GAP	16	-0.162	2.197	-4.988	-0.882	1.167	2.676	ESI	16	101.456	7.797	82.2	98.171	105.679	111.558
Country: Ireland															
GAP	16	-0.914	5.287	-9.02	-5.339	3.246	8.322	ESI	16	101.456	7.797	82.2	98.171	105.679	111.558
Country: Italy															
GAP	16	-2.326	3.487	-10.317	-4.273	-0.663	3.21	ESI	16	97.793	8.966	81.575	92.24	104.069	110.025
Country: Luxembourg															
GAP	16	-0.373	1.814	-2.904	-1.563	0.384	4.182	ESI	16	98.324	8.443	86.083	92.1	104.625	111.5
Country: Netherlands															
GAP	16	-0.828	1.965	-4.779	-2.116	0.54	2.779	ESI	16	100.003	9.068	80.617	96.06	105.619	114.233
Country: Spain															
GAP	16	-5.236	5.305	-12.833	-9.396	-0.483	2.298	ESI	16	97.411	9.785	80.275	89.806	105.11	109.158
Country: Sweden															
GAP	16	-0.463	2.209	-5.18	-1.888	0.491	3.72	ESI	16	100.296	8.012	83.383	95.192	107.812	110.008

Appendix 3.2: *Summary statistics for GAP and ESI on a country level (2005 – 2020).*

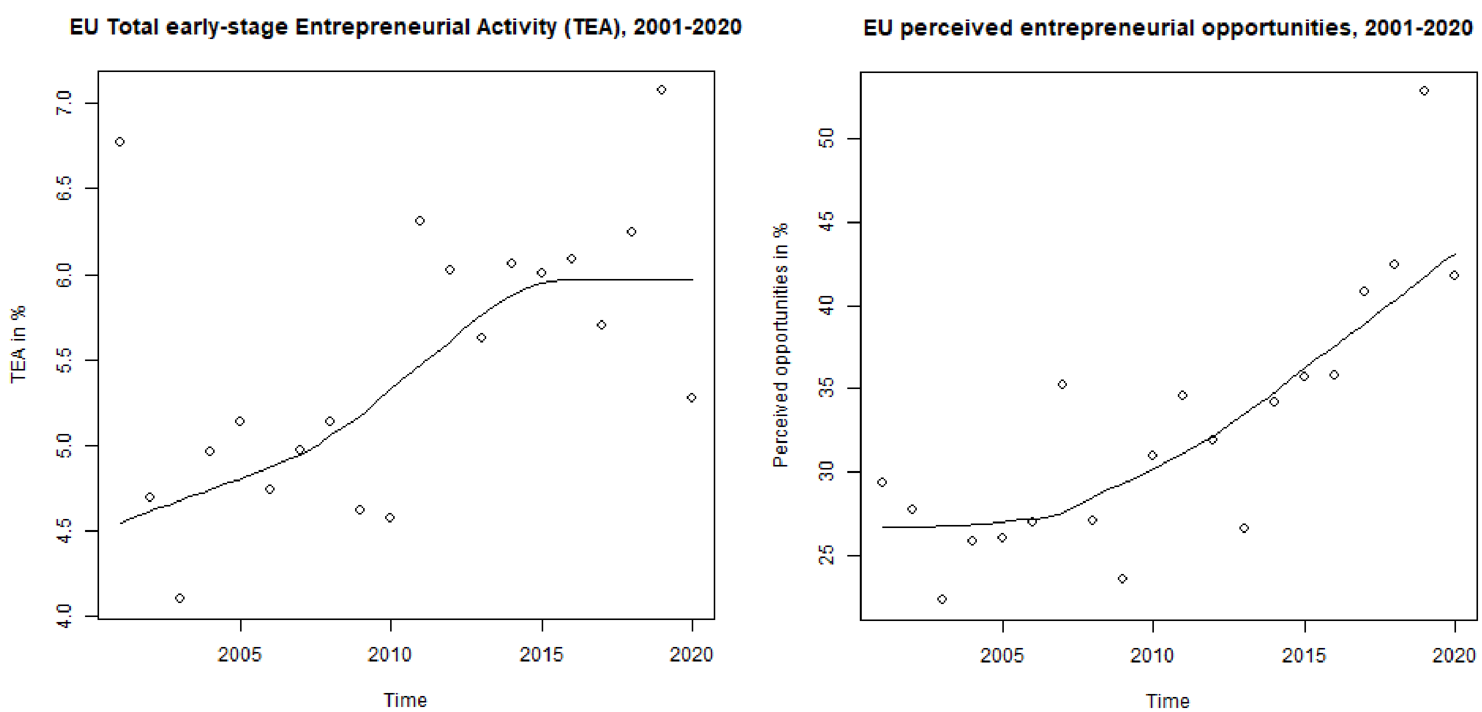




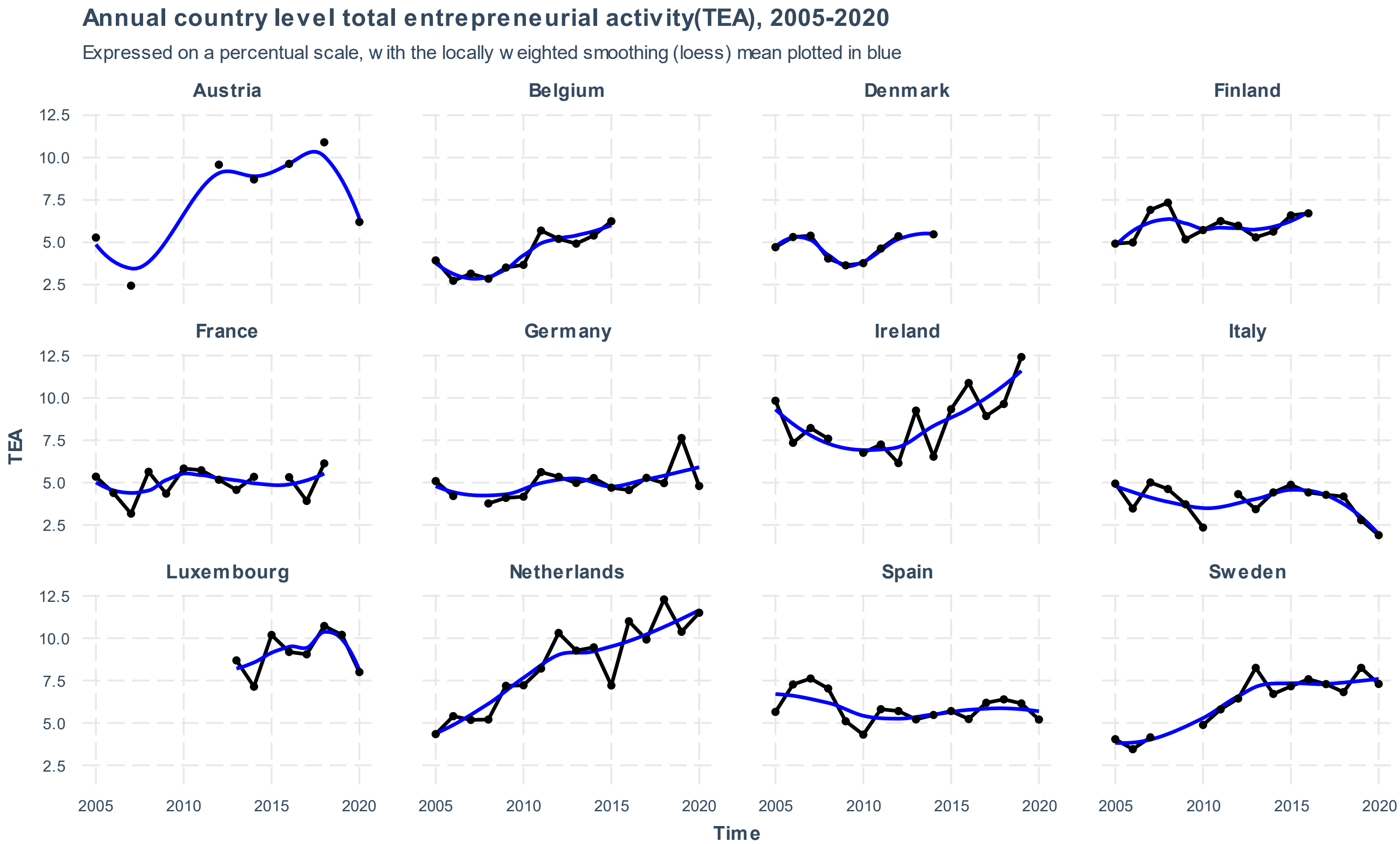
Appendix 3.3, *Individual country plots and overall trend boxplot for firm R&D spending (R&D spending).*

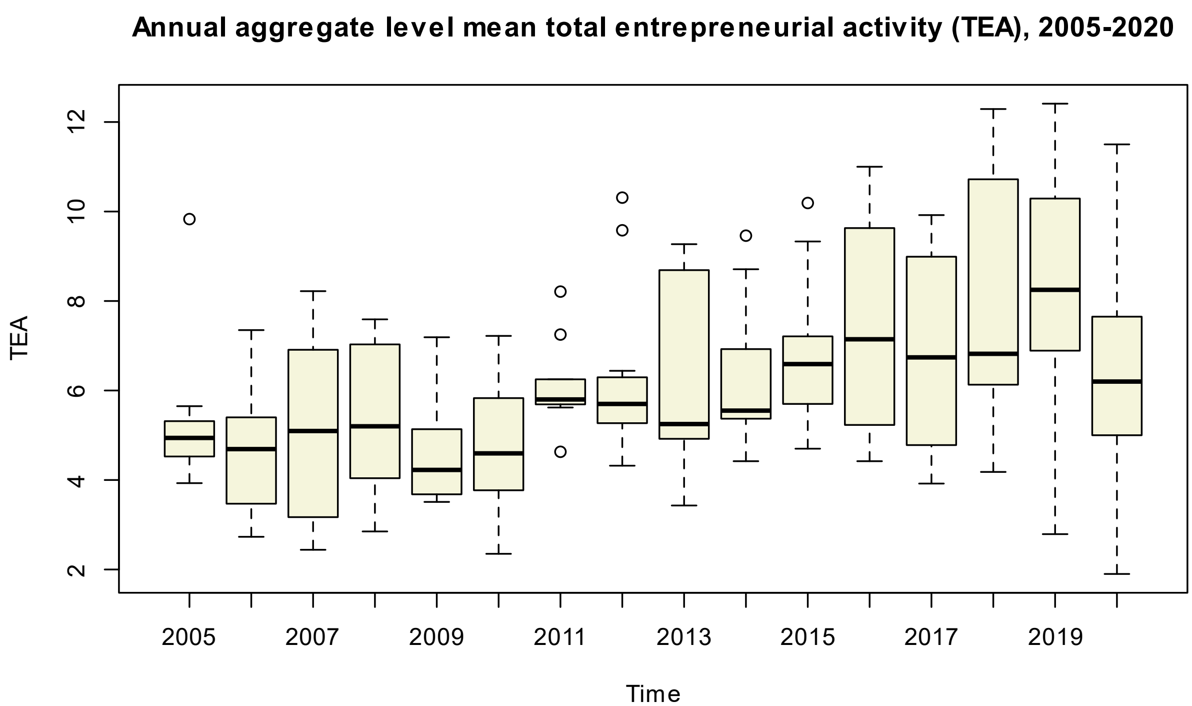


Appendix 3.4: *The relevant survey coding for the TEA rate metric (source: GEM)*

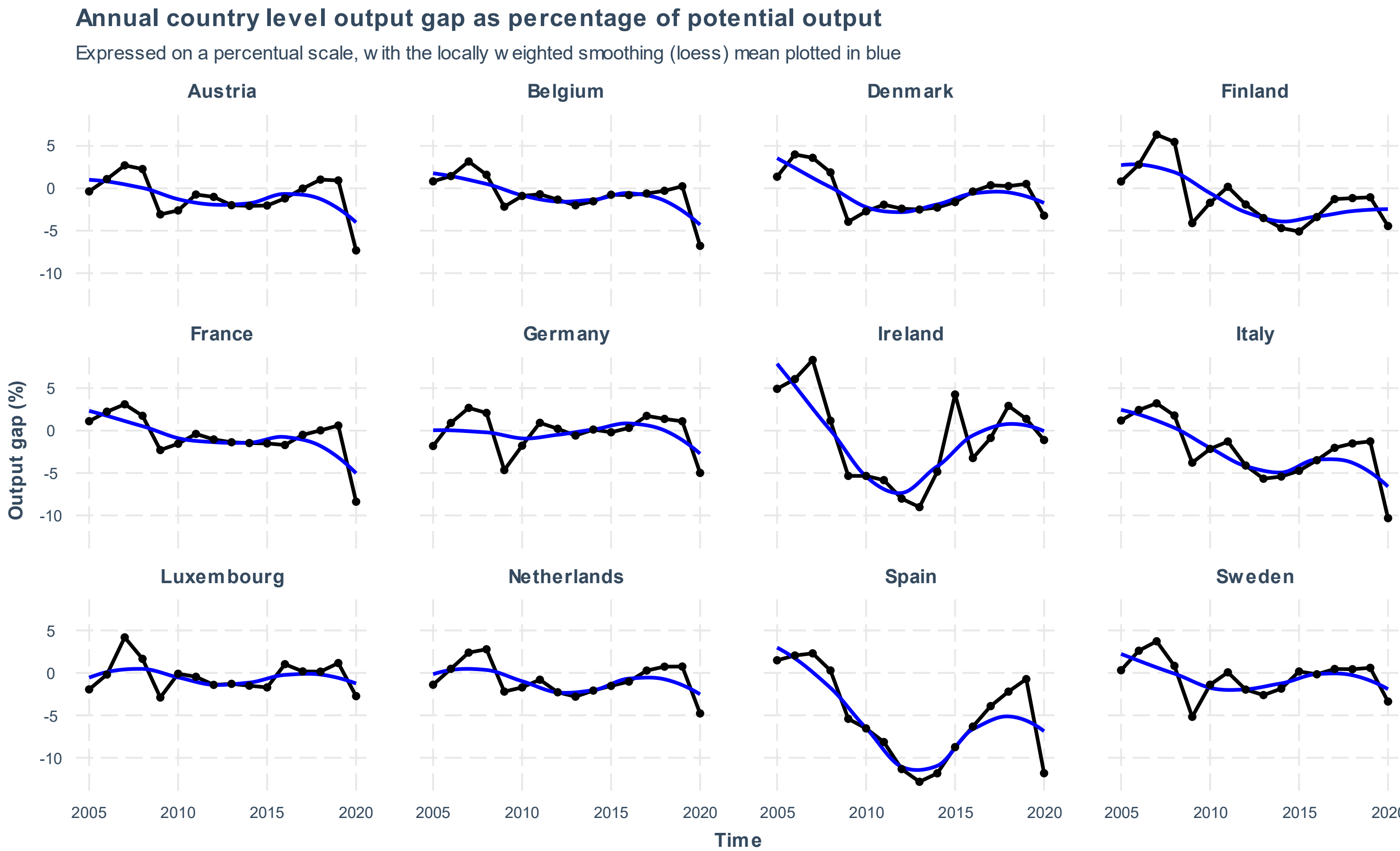


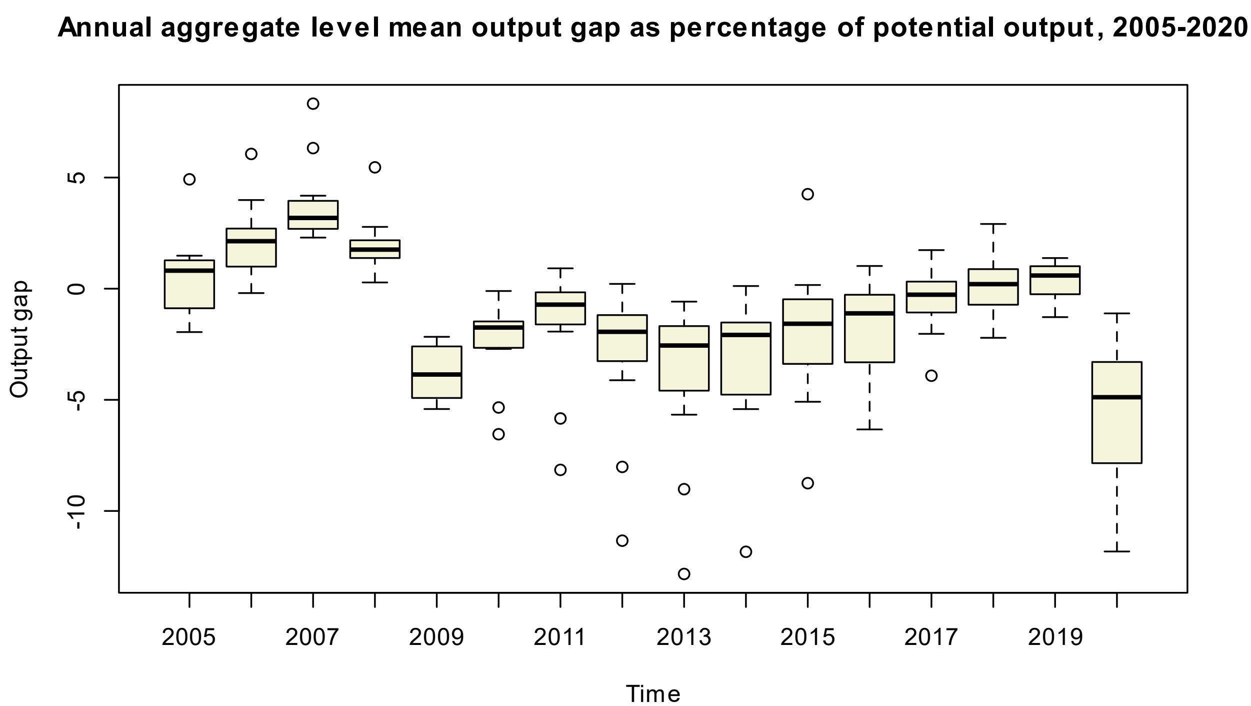
Appendix 3.5: *Scatterplots with trendlines of the EU aggregates for TEA and (PeOpp)*



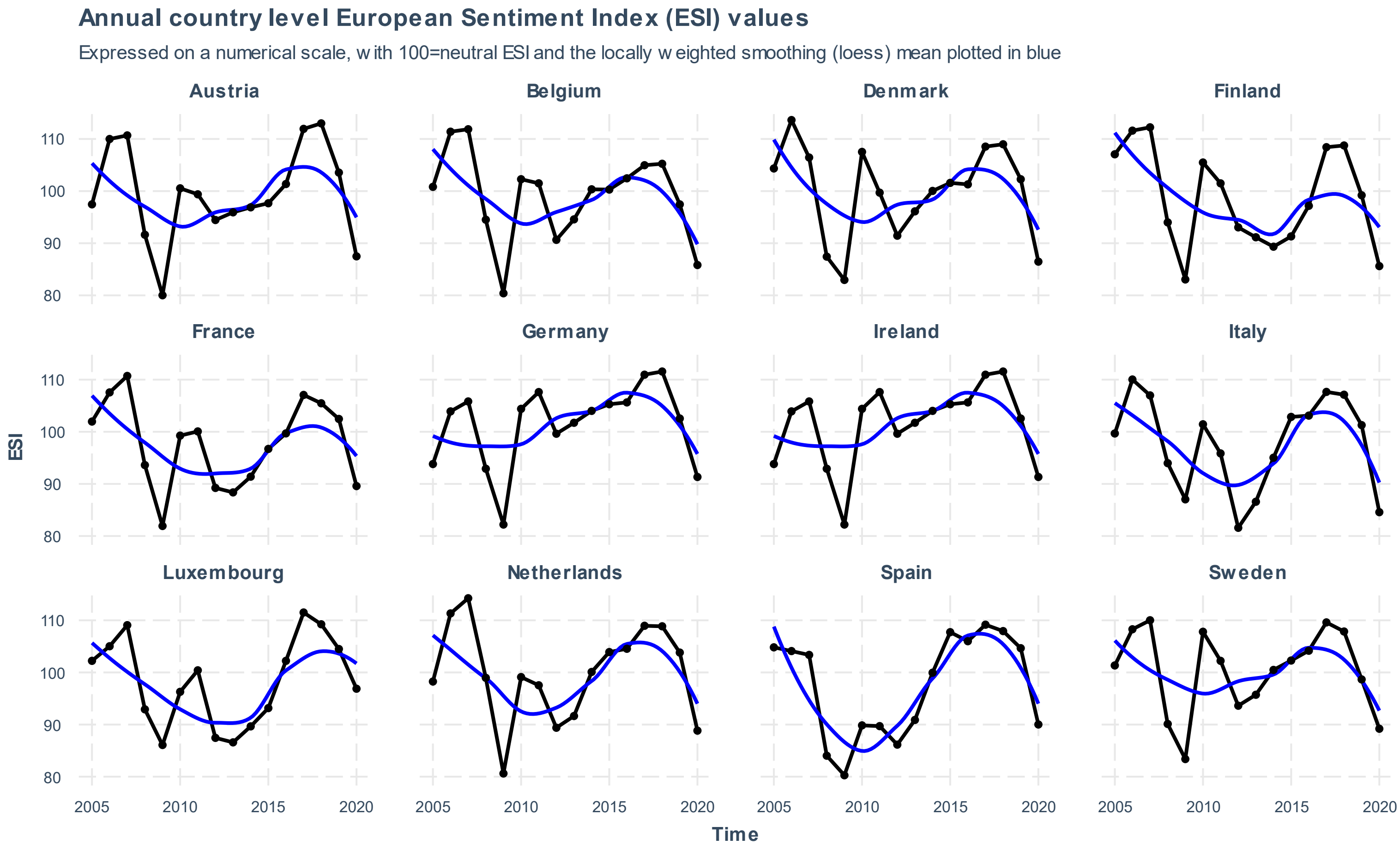


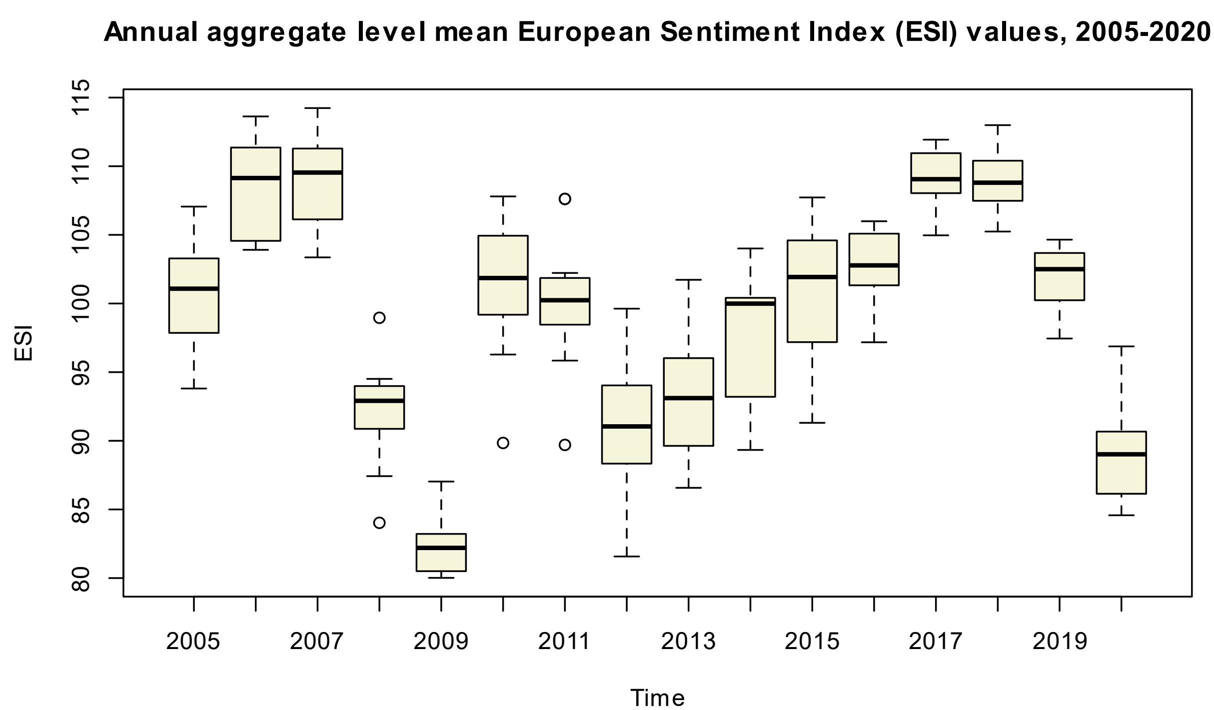
Appendix 3.6, *Individual country plots and overall trend boxplot for total entrepreneurial activity (TEA).*





Appendix 3.7, *Individual country plots and overall trend boxplot for the output gap (GAP).*

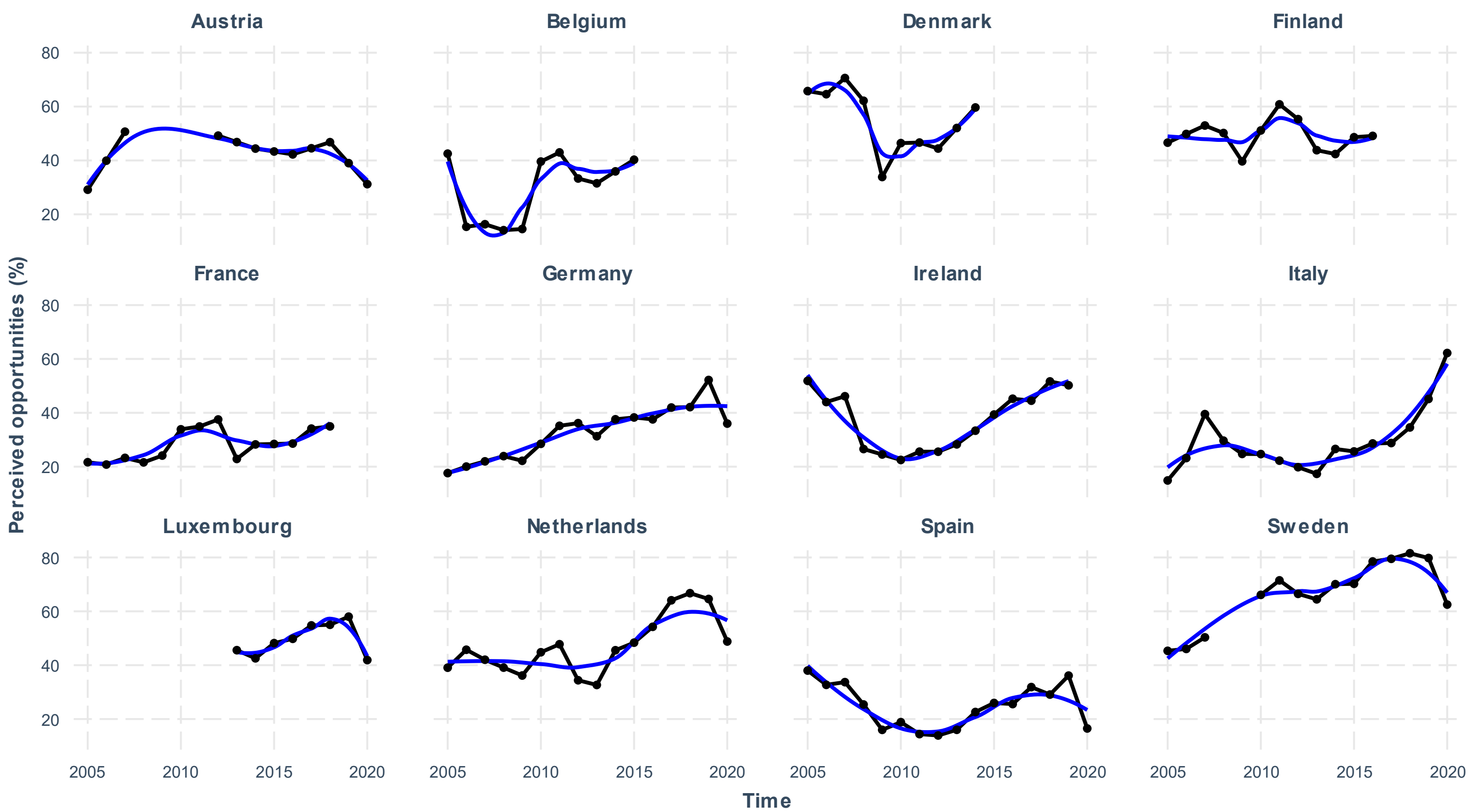




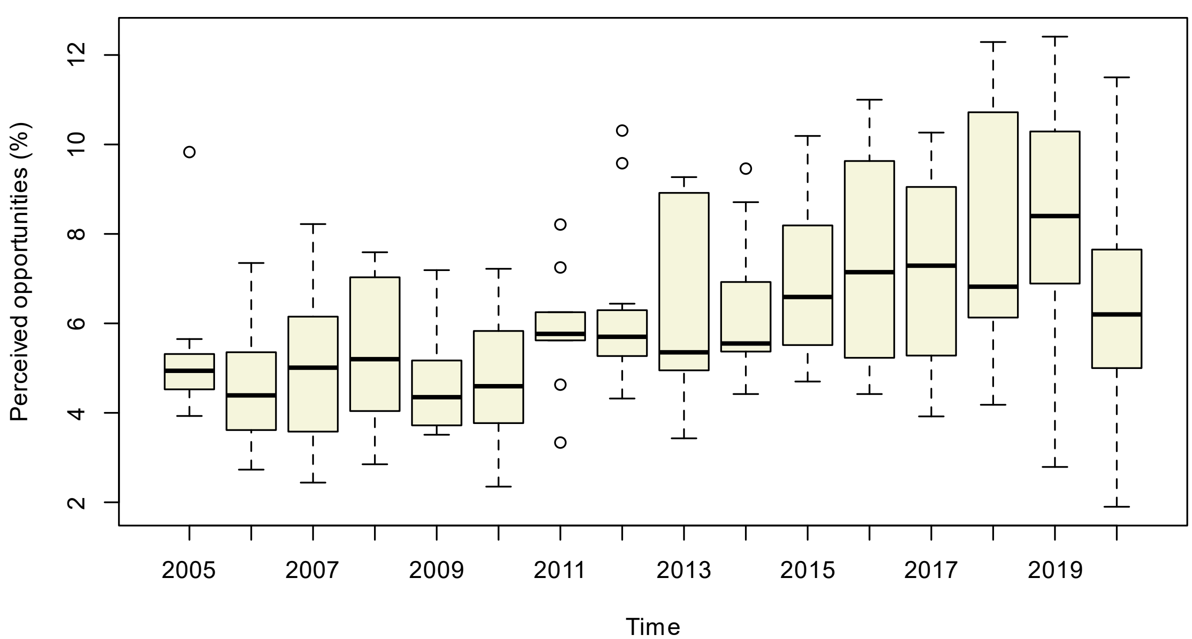
Appendix 3.8, *Individual country plots and overall trend boxplot for the European Sentiment Index (ESI).*

Annual country level perceived start-up opportunities, 2005-2020

Expressed on a percentual scale, with the locally weighted smoothing (loess) mean plotted in blue



Annual aggregate level mean perceived start-up opportunities, 2005-2020



Appendix 3.9, *Individual country plots and overall trend boxplot for perceived start-up opp. (PeOpp)*

Im-Pesaran-Shin unit-root tests

Ho: All panels contain unit roots — Number of panels = 12

Ha: Some panels are stationary — Number of periods = 16

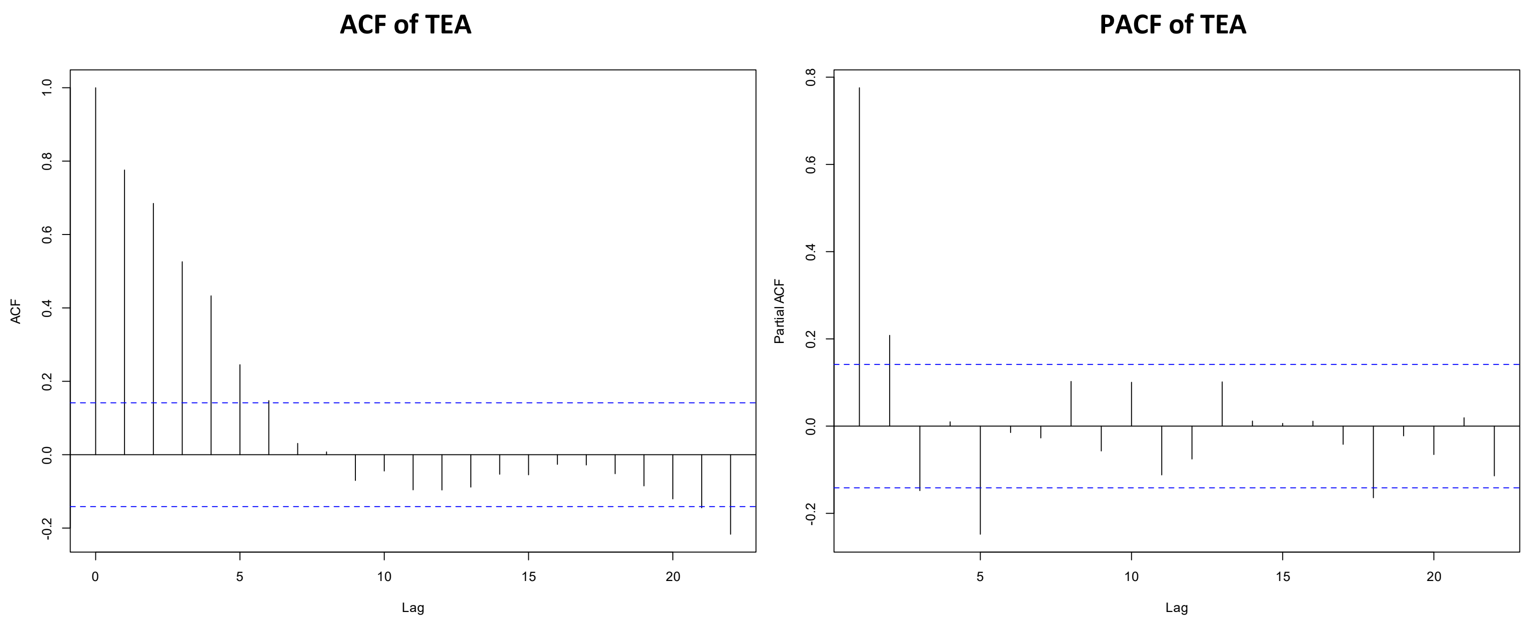
AR parameter: Panel-specific — Asymptotics: T, N -> Infinity sequentially

Panel means: Included

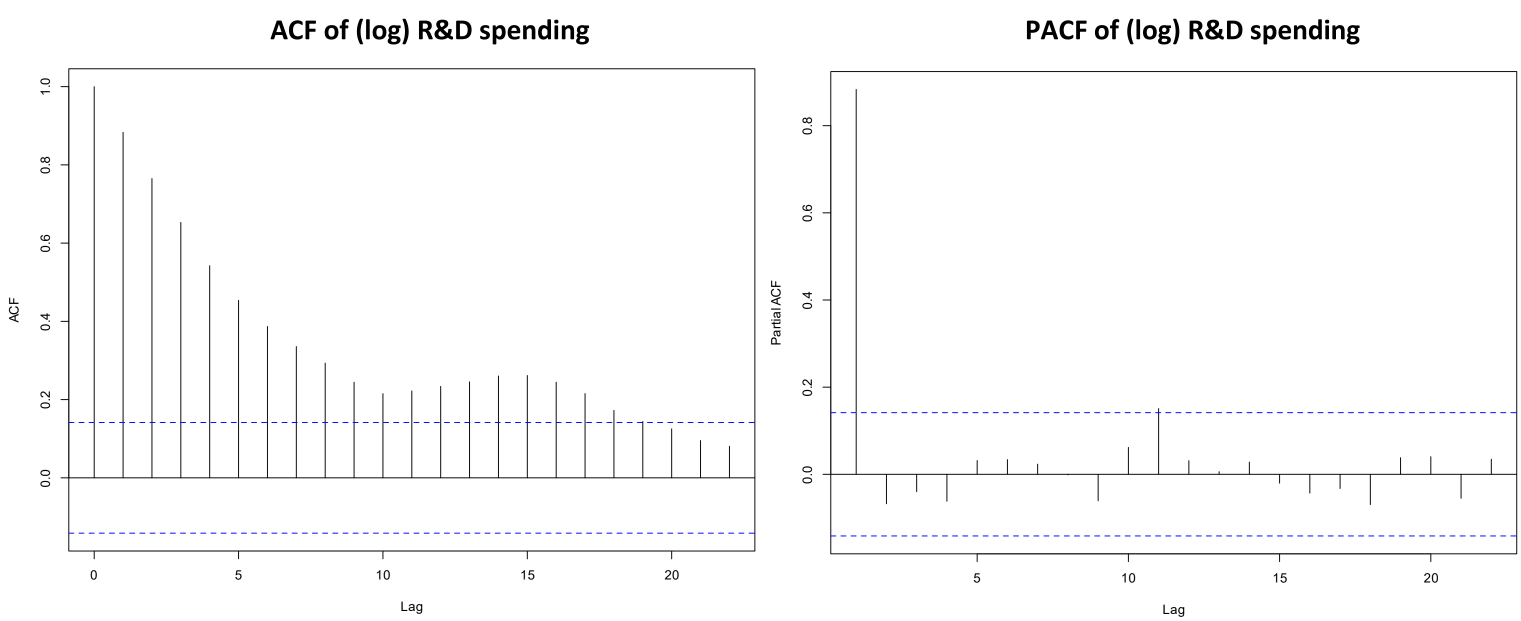
Time trend: Not included — Cross-sectional means removed

		Statistic	p-value
GAP ADF regressions: 1.50 lags average (chosen by HQIC):	W-t-bar	-0.2967	0.3833
PeOpp ADF regressions: 2.50 lags average (chosen by HQIC):	W-t-bar	-5.5554	0.0000
R&D ADF regressions: 1.50 lags average (chosen by HQIC):	W-t-bar	-3.5986	0.0002
ESI ADF regressions: 1.67 lags average (chosen by HQIC):	W-t-bar	-3.7319	0.0001
TEA ADF regressions: 1.25 lags average (chosen by HQIC):	W-t-bar	-3.9811	0.0000
GAP’ ADF regressions: 1.58 lags average (chosen by HQIC):	W-t-bar	-6.2072	0.0000

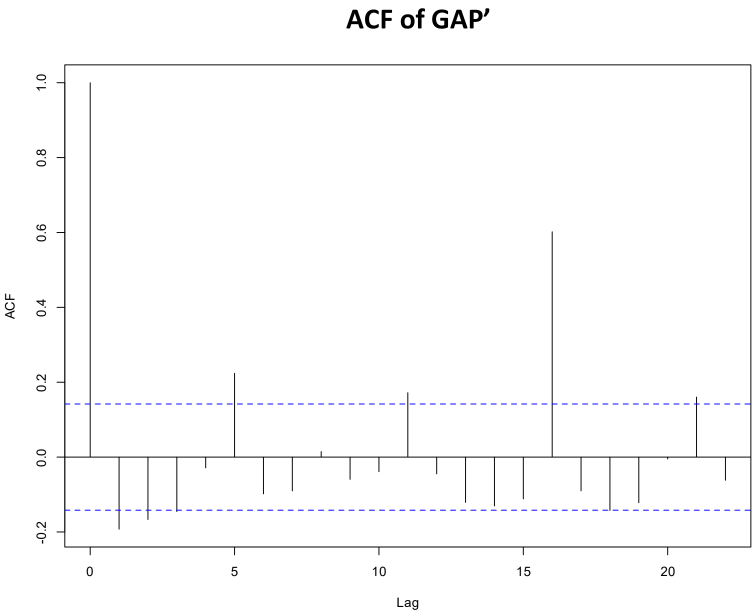
Appendix 4.1, *Im-Peseran-Shin (IPS) unit root test results.*

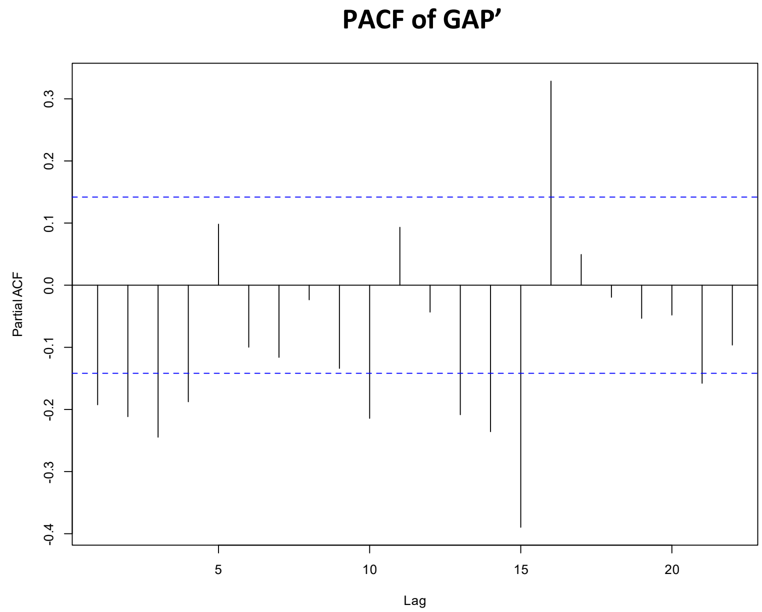


Appendix 4.2, *ACF and PACF plots for TEA, with the N. of lags on the x-axis and the 'noise' limits in blue*



Appendix 4.3, *ACF and PACF plots for R&D, with the N. of lags on the x-axis and the 'noise' limits in blue*





Appendix 4.4, *ACF and PACF plots for R&D, with the N. of lags on the x-axis and the 'noise' limits in blue*

Fixed-effect (FE) regressions with Driscoll-Kraay standard errors

VARIABLES	(4.1.) TEA	(4.2.) R&D	(4.3.) GAP’	(4.4.) TEA	(4.5.) R&D
TEA Lag (1)	0.108			0.0694	
	(0.0796)			(0.102)	
TEA Lag (2)	0.148			0.174*	
	(0.0974)			(0.0890)	
GAP’	0.0886	0.0254**		0.0719	0.0207***
	(0.0568)	(0.00831)		(0.0453)	(0.00572)
GAP’ Lag (1)	0.128***	0.00231		0.163***	-7.06e-05
	(0.0245)	(0.00891)		(0.0252)	(0.0155)
GAP’ Lag (2)	0.0410*	0.00365		0.109***	0.00374
	(0.0194)	(0.00341)		(0.0290)	(0.00749)
GAP’ Lag (3)	-0.0463			0.0287	
	(0.0494)			(0.0543)	
PeOpp	0.0252			0.0264*	
	(0.0141)			(0.0133)	
PeOpp Lag (1)	-0.00266			0.00478	
	(0.0183)			(0.0137)	
PeOpp Lag (2)	0.0181			0.0220	
	(0.0206)			(0.0205)	
ESI			0.275***	-0.0281**	0.00620
			(0.0344)	(0.0113)	(0.00412)
ESI Lag (1)			-0.0453	-0.0110	-0.00218
			(0.0273)	(0.0322)	(0.00400)
ESI Lag (2)			-0.0271	-0.0128	0.00291
			(0.0272)	(0.0271)	(0.00409)
ESI Lag (3)			-0.0469**	-0.0180	-0.00491*
			(0.0211)	(0.0213)	(0.00241)
(GAP-μ)*(ESI-μ)				-0.00727**	0.00102
				(0.00310)	(0.000779)
(GAP-μ)*(ESI-μ) L. (1)				0.00379	0.000173
				(0.00280)	(0.000431)
(GAP-μ)*(ESI-μ) L. (2)				0.00469	0.000486
				(0.00472)	(0.000494)
Year	0.000752	0.00995	-0.146**	0.0325	0.00901
	(0.0374)	(0.00579)	(0.0527)	(0.0607)	(0.00749)
R&D Lag (1)		0.600***			0.601***
		(0.0999)			(0.101)
Constant	1.844	-18.06	278.1**	-55.68	-16.39
	(74.18)	(11.36)	(104.5)	(119.8)	(14.50)
F-statistic	119.48***	112.27***	72.26***	58.33***	427.47***
Within R-squared	0.3777	0.7294	0.6083	0.4309	0.7457

Appendix 4.5. Standard errors in parentheses | *** p<0.01, ** p<0.05, * p<0.1

Arellano-Bond dynamic panel-data estimation (GMM)

VARIABLES	(4.1.) TEA	(4.2.) R&D	(4.3.) GAP’	(4.4.) TEA	(4.5.) R&D
TEA Lag (1)	0.0601			0.0733	
	(0.0988)			(0.112)	
TEA Lag (2)	0.111			0.179	
	(0.113)			(0.136)	
R&D Lag (1)		0.621***			0.607***
		(0.0589)			(0.0627)
GAP’	0.0891	0.0264***		0.0380	0.0148***
	(0.0547)	(0.00284)		(0.0405)	(0.00522)
GAP’ Lag (1)	0.127***	0.00575	-0.186***	0.151***	-0.000995
	(0.0382)	(0.00504)	(0.0343)	(0.0562)	(0.0133)
GAP’ Lag (2)	0.0412	0.00583		0.0822*	0.00210
	(0.0311)	(0.00589)		(0.0429)	(0.00404)
GAP’ Lag (3)	-0.0420				
	(0.0309)				
PeOpp	0.0275			0.0344	
	(0.0269)			(0.0256)	
PeOpp Lag (1)	0.00178			0.00974	
	(0.0112)			(0.0118)	
PeOpp Lag (2)	0.0229			0.0119	
	(0.0188)			(0.0144)	
ESI			0.245***	-0.00524	0.0102***
			(0.0272)	(0.0184)	(0.00200)
ESI Lag (1)			-0.0146	-0.0241	-0.00239
			(0.0206)	(0.0304)	(0.00359)
ESI Lag (2)			-0.0448**	-0.00829	0.00325
			(0.0198)	(0.0252)	(0.00336)
ESI Lag (3)			-0.0660***	-0.00624	-0.00510**
			(0.0158)	(0.0156)	(0.00216)
(GAP-μ)*(ESI-μ)				-0.00691**	0.00113**
				(0.00328)	(0.000480)
(GAP-μ)*(ESI-μ) Lag (1)				-0.000624	-0.000253
				(0.00455)	(0.000825)
(GAP-μ)*(ESI-μ) Lag (2)				0.00235	0.000219
				(0.00335)	(0.000503)
Constant	3.453***	1.884***	-12.22***	7.148***	1.346***
	(0.696)	(0.318)	(3.920)	(1.189)	(0.463)
Wald chi2	124.30	466.65	464.76	79.72	11975.65
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000

Robust, clustered (country-level) standard errors in parentheses

Appendix 5.1. *** p<0.01, ** p<0.05, * p<0.1