POLITECNICO DI TORINO

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M.Sc. thesis work

Team composition influence on decision-making process: scientific and effectuative approaches

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“Fortuna
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Content

Abstract

A number of scholars agree that entrepreneurial activities lead implicit high risks and therefore would deserve a deep study (Forlani & Mullins, 2000; Ping, 2004; Eisenmann et al., 2013). A crucial issue which must be faced nowadays is the high failure rate and strong difficulty in expansion by scaling the business. According to US Census Bureau, Kauffman Foundation and US Labor Department is reported that 87% of the startups abandon the entrepreneurial idea within seven years by the born (Fairlie and Miranda, 2017). Yet, the Thompson Venture Economics showed that the 55% of startups receiving first financing round gets failure with economic loss, whereas only the 6% is able to achieve financial return five times bigger the initial investment (Kerr et al., 2014). In order to put boundaries around the elevated uncertainty, the researchers advise the strategic agility utility which can derive both from structured (Ries, 2011; Camuffo et al., 2017) and more flexible approaches (Sarasvathy, 2001), so that in this thesis project the decisional-making methods named Scientific approach and Effectuation will be explored.

Into the experiment of interest analyzed in the following work, age heterogeneity resulted to be positively and highly linked to the variables of interest, which are both linked to the decisional process. It showed to be more influencing on scientific approach rather than effectuative behavior: this is to confirm that the experience diversity factor is deeply crucial for the scientific paradigm, since it puts roots on the continuous feedback exchange and test comparison, that is a process fostered by a good task conflict management, meant as the concept introduced by Jehn et al. (1997, 1999) in opposition to the relationship conflict management. Right such last point arises from the evidence about control variable called as Internal Network, which has given evidence that preexisting ties among team members can positively affect the decision-making process through a better relationship conflict management, thus mitigating divergences deriving from heterogeneity. Instead, the ambiguousness of the findings regarding gender differences underlined the primary doubts claimed in the wide literature (Phillips & O'Reilly, 1998) produced on the argument, anyway the prominent relationship conflict management weight suggested by a number of different authors (Jehn et al. 1997; Klotz et al., 2014; Fitzgerald et al., 2017; Zhang, 2019) is here confirmed, thanks to what found on the internal network variable and its mitigating effects. Yet, the startup team numerosity is instead an evident proxy of how many external ties the team is potentially able to achieve: the more the team members are, the more they could merge their different contacts with the aim of creating a stable and loyal business network. Referring to what written in the recent study of Alessandri et al. (2018), the work engagement has been tracked and resulted as statistically significant throughout all the regression models, with positive influence on both natural levels of scientific and effectuative approach. Additionally, as discussed by Amit (2001), also the prior experience in business plan

writing demonstrated to be influencing, thus proving a real tie between the practical business plan experience and the capabilities needed in the effectuative framework. Also differences in decisional processes were expected when keeping the offering kind and industry type as reference (Schleimer & Shulman, 2011), maybe due to the physical nature of product vis-à-vis the more abstract service concept. Here the offerings appear being positively correlated with the sole scientific approach when they are services. It can be due to the fact that the flexible nature of the services makes easier to create continuous feedback exchange with market and customers, so that phases of test and validation come to be facilitated thanks to the possibility of completing the entire process by only using online means, with consequent less time wasting and more efficient learning. Yet, Mitchell and Shepherd (2010) proved that decision-making tends to be excessively risky and inconsistent when acting in more dynamic industries: our results seem to partially corroborate their findings, because belonging to the software industry negatively related to the sole innate effectuation degree.

Excellent significance is guaranteed ($p<0.01$) by the boolean indicating when team majority is engaged with a M.Sc. - it is positively linked to both innate scientificity and effectuation, therefore an high academic level in progress can provide the needed technical insights to conduct appropriate test phases and use right data validation tools (scientific approach), along with offering the amount of experience necessary for balancing abilities of execution, network, control and flexibility. Yet, according to Chatterji et al. (2019), too high academic achievements make become resistant to the capabilities needed in the effectuation framework: this is what arised from who already obtained a Master post-lauream or PhD, since these two dimensions negatively related with effectuation. The top university levels seem to negatively influence the natural effectuative approach maybe because the latter puts roots on flexibility, execution, and practical experience, namely features being often stiffened and obstructed by extremely high levels of standard academic education. In the end, the accumulated experience is difficult to replicate and allows entrepreneurs to understand competitive structure and market strengths, quality standards and most profitable trends. It improves capability of performing more precise predictions, along with diminishing the usually observed effects of discouragement that emerge after the initial instants. The outcomes from STATA indicate that correlation exists and always presents positive verse. By using the team as reference, the average amount of different industries in which members have cultivated direct experience is strongly linked to higher values of scientificity and effectuation; such is consistent with what described in literature, namely the effectuative approach is someway strictly linked to the experience dimension. Yet, the fact of already having established some firms or experienced business plan writing positively correlates with the sole innate effectuation degree. Again, this is to give evidence about the prominent experience weight on the effectuation framework, while showing its inferior influence on the natural scientific approach.

The Blau's gender index finally showed significant negative correlation with the natural scientific approach, looking like such difference leads worse relationship conflict management which outperforms the benefit coming from a better task conflict management. The effect does not keep the same within the specification where effectuation is treated: this is to corroborate that heterogeneity has largely more influence on the structured dynamics of feedback exchange which characterize the scientific paradigm, while are not a central driver for the natural effectuation level. Indeed, the effectuative method pays more attention to enough abstract abilities such as network, control, execution, and flexibility, less suffering the effect brought by task conflict and relationship conflict management. These results perhaps confirm the intuitions proposed by Carr (2010) and Tinkler (2016). The first paper found that decision-making process can be affected by concerns about stereotypes and identity devaluation, rather than attribute gender differences to innate and stable factors. Tinkler instead decided to investigate venture capitalists' funding decisions in high-growth and high-tech entrepreneurship, so discovering that women were supposed to be less competent and having less leadership ability when available information was insufficient. The findings thus suggest for gender differences not linked to actual personal features, but rather to prejudices and social inequality; in other words, they warned about a sort of self-fulfilling prophecy at basis of the phenomenon.

The totality of the analyses executed in this thesis work took into consideration a sample composed of 305 mainly Italian startups, with a total of 542 entrepreneurs; the following project will contribute to the poor literature already existing about this topic, so that further analyses will be encouraged in order to provide useful suggestions for scholars, with the final objective of fostering the Italian entrepreneurial scope and economic system. In light of the outstanding and superior performances registered by startups applying scientific and effectuative approach – as furnished in literature above all by Camuffo et al. (2017) and Sarasvathy et al. (2001, 2003) – this thesis work brings to conclude that the institutional bodies as well as more technical entities (e.g. government, universities, accelerators, incubators and so on) should promote the most balanced entrepreneurial team compositions, so as to foster the positive impacts that are likely to be observed on decisional activities.

1. The Decision-Making process

During the last years, the entire economic world participated in the continuous increase of new ventures launches, a trend surely supported by the lately introduced working way in the high-technology industries. Indeed, every day many firms arise to follow the current agile growth rate of the global entrepreneurial ecosystem, trying to acquiesce to the high standards and competitive habits dictated by market demand. Thus, a so quickly growing system implies an ever-increasing complexity in various aspects: extremely high competitiveness along several segments of customers, huge complexity in understanding and applying technical discovers, ambiguous outcomes deriving from ability in gathering and interpretating data from heterogeneous and diverse sources, difficulty in elaborating the psychological and personal features coming from each individual personality and, therefore, finally the role that every CEO (or founder, or co-founder team, or decision-maker in general) has in the corporate success or collapse. In light of the above, this study - as many others present in literature - aims to investigate more deeply the potential patterns and frameworks existing in the way by which new firms (i.e. startup) arise, develop, and possibly die.

One of the most relevant factors many scholars and researchers characterized as influencer of enterprise dynamics is mainly the decision-making process, involved in the birth and enhancement of the businesses, since such key circumstance is critical to adapt proactively the corporate attitudes and features to the market advancements, in terms of offering, marketing activities, as well as quality requirements, design, usability, cost structure and price. The entrepreneurial activities lead implicit high risks and deserved a deep study dedicated by a number of academics. Forlani and Mullins (2000), for instance, stated that the main components affecting entrepreneurial risk perception lie in three aspects, that are the investing sum of fund, potential loss and uncertainty of anticipated outcome (i.e., the more capital the new firm demands, the higher variability in expected result is assumed, therefore greater odds of economic losses and higher risk degree perceived by entrepreneurs. It is relevant keeping in mind that certain types of personality traits can account for the majority in a team, but strategic decisions require for not-individual processes: interactive discussion is needed (Ping, 2004), however considering that single influences (complying to common rules) affect overall outcome. In the recent literature two different currents established in the decision-making framework, in order to better interpret and draw the entrepreneurial attitudes: heuristic search (McGrath, MacMillan, 1995; Shepherd et al., 2012; Sarasvathy, 2001) - among which emerged the Effectuation approach suggested by Sarasvathy (2001) - and a more rigorous and systematic one, named scientific method (Eisenmann et al., 2013; Ries, 2011; Camuffo et al., 2017). This thesis project will focus on the two different standpoints just cited, since they represent the attempt to manage and accommodate a continuously evolving and complex

economics, respectively by incessantly modelling (and adapting) the entrepreneur's strategies to the scope on one side, and by implementing a rigorous (and faultless) method on the other side. A recent research of Barron and Amoros (2019) highlighted how entrepreneurship education for scientific communities is increasing as importance and common attitude, thereby turn research activity into marketable products. Their article analyzes the entrepreneurial program named NoBI offered to scientists in Mexico, thanks to the support of business and technical experts; it was aimed to validate business ideas (exactly as done in scientific approach) and construct a consistent business model framework. The final outcome observed was the improvement due to the program along both the two dimensions.

The great attention assigned to certain dynamics is only a facet of a spreader movement affirming in the new emerging economies: many studies, as those realized by Koekemoer & Kachieng'a (2003), underlined the importance of boosting the entrepenurial ecosystem given its critical role in the national welfare, other than for the sociological, philanthropic and financial implications. In addition, recent researches demonstrated the prevalence in weight (for the emerging economies as well as countries like Italy) of startups and small & medium enterprises (SMEs) as main economic drivers in the local context: during the last decade of the 20th century, several scientific parks, innovation hubs and incubators arised, that is, renewed attention to technology innovation and new services/products development has incited the growth of new companies; such phenomenon almost never calls for a solo effort, so that it requires innovation management, along with startups' environment care and financing. Right such last aspect is often the main reason why it is crucial creating a targeted approach and structured co-ordination, fighting against the criticality represented by the lack of proven business track records, which is a constraint making strongly reluctant the funding groups in giving trust to the new enterprises; a further issue is the need of expertise in running the new emerging technologies and startups, other than the necessity to generate an actually unique competitive global environment.

1.1 Innovation and entrepreneurship overview

Every entrepreneurial activity, in light of the considerations expressed in the above paragraph, is marked by a strong presence of risk, uncertainty and complexity. These factors are more crucial if we consider a particular type of entrepreneurship present in the current landscape: the so called "start-up" ventures or, more in general, the high technology-based enterprises. Indeed, neglecting of the legal definitions of such entities (i.e., in terms of "innovative" formal definition, average education level gained by the co-founders team, income flows, business' years of life, original patents exploitation, and so on), at the centre of the analysis proposed are located all the new ventures able to concretely contribute for the technological development, through the use of new methods, thinking ways, applications and

innovative products/services in order to meet the ever increasing market needs. Given the definition of the object of study, it is easy to understand that the scenario in which it plays is characterized by still growing uncertainty, the major cause of failure nowadays: so that, Effectuation and Scientific methods raise as possible solutions, providing strategic agility and pre-set decision making, which aim to quickly adapt to the conditions mutation although by using very different proceeding ways.

A number of eminent works (e.g. Van de Ven, et al., 1984) deeply analysed the key success factors at the basis of startup success. A whole comprehension of the startups' development phases is considered as fundamental (Pugliese, et al., 2016), thereby better handle and coordinate them toward the success moment. Nowadays, the centrality of the entrepreneur role within the society is proven by a number of data, coming from different sources reachable on the web, that confirm the importance of nourishing the business fabric. Many academics operative in the sector gathered a lot of evidences about economic indicators; e.g., Urbano & Aparicio (2016), and so also Valliere & Peterson (2009), stated the new ventures, through the creation of workplaces, prominently contribute to (not only) economic wellness of both the countries and local areas where they arise and progressively expand. Yet, it is interesting to highlight how the failure reasons, referring to the startup world, are polarized towards few elements. In fact, the analysis was carried out only on US startups, but the results appear to be consistent with what is expected also in other geographical clusters. According to the wide Fairlie & Miranda (2017) study, realized by getting information from U.S. Bureau of Census, Kauffman Foundation and U.S. Department of Labor databases, a sample of around 581K startups was analysed: they found that as much as 85% of the total new ventures decided to abandon their own entrepreneurial idea within seven years (of the activities begin) and never hiring employees. Yet, as reported into an article of 2017 on Forbes website (which grasped data from CB Insights and Statista), and later cited by EU-Startups (2018), there is common agree that the main reasons of startup failure are lack of market demand, inconsistency between team and faced business, cash burn ignoring.

Instead looking again at new ventures but in more advanced growth phases, Kerr et all (2014) studied a sample, by exploiting the Thompson Venture Economics dataset, composed of only startups which already have received a first funding round. The researchers found that 55% of the total closed the activity and made it with economic loss, whereas only the 6% gained financial returns of 5 times the starting obtained investment. Furthermore, such 6% accounts for the majority of the gross income registered through the entire study, signalling an extreme and excessive disproportion in the distribution of economic success, namely of the quality about entrepreneurial ideas and, still more important, their execution. In light of the above, the overview presented on the innovative entrepreneur role, and the field where he plays, is enough complex and difficult to interpret. The contribute brought to the economic system is recognized, nevertheless the criticality

encountered in the patterns analysis and in measuring various attitudes and behaviors make challenging a whole comprehension of the phenomenon, so that - seen the huge innate and intrinsic uncertainty conditions too - provoke the high failure rates observed by using the governmental data as means.

1.2 Scientific Method

The author and American entrepreneur Eric Ries attempts to find an answer by declaring that each startup, given the uncertain and unpredictable scenario where it must compete, has to introduce a new and revolutionary approach in the decision-making process for its own routines. Indeed the success (or failure), as result of long period performance, is an outcome deriving from a pre-set and systemic strategy, that is, it never arises only thanks to genetic heritage or lucky contingencies. Ries (2011) tends to stress more and more times on the concept of uncertainty, that each entrepreneur (differently from managers e.g. CEOs, directors, admins) has to face starting from his venture's first day of life. According to what already said, the statement done by Freedman (1992) many years ago makes sense: the uncertainty factor plays a crucial role in the choice and management of every-day entrepreneurial activities, so that it requires deeply diverse decision-making tools, if compared with the canonical ones usually used in certainty and risk conditions. Consequently, it appears of fundamental importance to make distinction between risk and uncertainty. One of the first academic helps in this direction is offered by Knight (1921), who defined the "risk" word as a quantifiable phenomenon, of which we have no certainty about the fact it will happen, but its frequency is computable in statistical terms through the means offered by the probability distributions. Instead, the "uncertainty" is an event of non-quantifiable nature, namely of which it is impossible to make conjectures about probability distributions too. Thus, the evident difference is that, in the first situation, the difficulty can be mitigated thanks to imprecise esteems extracted from the historical series; meanwhile, looking at the uncertainty definition, we observe the added requested effort brought by the lack of previous experience in equal (or similar) activities and equal (or similar) boundary conditions.

The classic managerial techniques based on *ex-ante* and deep study of problem and scope, so trying to derive the probability distribution and better predict the right development to follow as well as the potential results: therefore, they act in situations of risk and are ideal to such frameworks; yet, in case of issues characterized by really high uncertainty, an *ex-post* approach would result useless and impossible by definition on one side, but by the other side the classic techniques require for making too strong assumptions, leading to solutions founded on erroneous basis. Finally, the answer to the largely uncertain entrepreneurial scenario can be found in a more adaptive method, the so-called strategic agility suited for quickly adapting to the events mutation. Consequently, the possible solutions proposed in this thesis project are two: heuristic search (McGrath, R.G., MacMillan, I.C., 1995; Sarasvathy, S.D., 2001; Shepherd, D.A. et al., 2012) - thought

to better mitigate and deal with situations by exploiting specific ad hoc tools - and the scientific method (Ries, E., 2011; Eisenmann et al., 2013; Camuffo, A. et al., 2017), which looked at routines used by researchers and academics.

The Scientific approach puts its own roots onto the methodologies cultivated by scientists and researchers (Camuffo et al., 2017; Ries, E., 2011; Eisenmann et al., 2013), just like scholars and several types of science professionals, who use it in order to better observe, analyze and understand the phenomenon taken into consideration. Eisenmann et al. (2013) showed the superiority of scientific approach adapted to business experimentation rather than other methods; Kerr and colleagues (2014) believed that scientific experimentation was central within the entrepreneurial decision-making, as knowledge is not fully accessible in advance and cannot be deduced from set of first principles. Such widespread mindset, highly diffused in academic environment, is appropriate to be exploited as a general research criterion, therefore also relevant in the decision-making sphere. It is based on the systematic path followed throughout every scientific experiment, beginning from a set of initial conjectures (in this case, the actual starting point is the entrepreneurial idea) with the purpose of finding acknowledgement from the real world and, if needed, starting again after having gathered the feedback and setted again the flow. Analogously, it is possible to recognize the four primary components of the process, namely:

1. formulation of a solid theory, created thanks to deep studies of the scope and previous events, experienced by the same entrepreneur as well as predecessors who worked in similar industry and/or under similar boundary conditions;

2. creation of reliable and falsifiable hypotheses suited to be successively tested, with the goal of trying to understand and finding confirmation/refusal on specific and precise aspects of the business and/or entrepreneurial idea, so as to avoid wastes in terms of resources and time, highly limited by definition in the analyzed scope;

3. testing such hypotheses, by using the right methods and tools to interpretate and elaborate the data, focused on introducing no distortions into the experiment design, so that the outcome is consistent and solid as much as possible;

4. continuous and iterative validation (that is, probably the most important side of the process) of the feedbacks gathered from market, target customer, offering kind and, more in general, from the whole competitive ecosystem, paying attention to potential both perceptual and psychological biases - very common even if at high academic levels - which may move the results toward a direction far from the exact reality interpretation.

Since 2017, because of the RCT (Randomized & Controlled Trial) conducted by Camuffo and his team on an early-stage startups sample, the research community can count on a new fundamental contribute about the scientificity applied to the decision-making paradigm, given the fact he realized the empirical measure of its impact: Camuffo et al. (2017), from Bocconi University of Milan, demonstrated the positive correlation between scientificity level and i) frequency in abandoning the fallacious initial entrepreneurial ideas, ii) numbers of pivot (i.e., logical consequence of a negative outcome resulting from the validation process, signalling the Scientific method has been properly followed by the entrepreneur, placing the real evidences prior his own convictions) carried out, and iii) level of startup performance. Such outcome is consistent and due to the greater precision and accuracy provided by the scientific mindset cultivated throughout the entire development, with the appropriate methodologies and tools: this makes easier to detect inadequate projects after reduced time bucket, improving the odds to pursue the successful ones. More exactly, it increases odds to pursue ideas with false negative returns.

Ries (2011) described the scientific approach as a Build-Measure-Learn cycle, ending with product improvement, changing strategy or changing vision; the decisions however bring new implementation, experiment and then learning. The Build phase puts its own roots into the hypotheses formulated by the entrepreneur, and is usually realized through MVP (Minimum Viable Product), focusing on the minimum resources consuming. Then it comes to pivot the idea or proceed with Measure, the central phase in which information and data are generated. Furthermore, here the entrepreneurs has to define metrics and validation threshold. Then, into the Learn step, Ries describes the traits of a critical interpretation based on evidences: the final outcomes drive to pivot the idea, confirming the business model or dropout.

Other scholars, like Gans et al. (2017), underlined the central role of the entrepreneurial uncertainty in both decisions about business selection and observed failure reasons. Zenger (2015) too elaborated that strategies cannot be mere trial-and-error processes. Thus, the validation phase has to be still more fundamental in the business conducting (McGrath, R.G., & MacMillan, I.C., 1995), so the literature provides entrepreneurs with scientific approaches to decision-making processes, among which the Lean Startup is one of the most recognized (Ries, E., 2011, & Eisenmann et al., 2013), founded on the Galilean thinking way regarding test and validation of ideas, with the purpose of learning maximisation in high uncertainty conditions. In particular, Vining (2013) defined it as an iterative process used for studying an unknown situation (e.g. a new largely innovative venture) and its intrinsic insecurity, by exploiting a set of procedures repeating throughout the time. The provisions to which submit are divided in four steps and, as mentioned in the above paragraphs, they are theory formulation, falsifiable hypotheses model generation, testing with respective data analysis and finally the

rejection/validation, always keeping into consideration the goodness and veracity of test and theory. The possible refusing provides us with the right insight and feedback needed to proceed for the complete review, so that the entrepreneur can be ready to start with a new development cycle. In the scientific approach, the steps conceived to be strictly followed are the core discriminating that distinguishes between good and bad enterprise path, while limiting the frequency of failures along the entrepreneur's route: so that, the way by which they are designed and mostly executed plays a critical role in the success of the idea. Looking with particular focus at them, it appears appropriate to specify that, during the theory creation phase, the entire team should be able to generate precise frameworks and elaborations about certain business facets deserving dedicated attention. For instance, the theory may be referred about a number of business model components, like target customer, product, cost structure (and so final price), marketing channels, distribution means, key activities, selling mode and main commercial/strategic partners; the more such procedures are well defined and clearly structured, the more the entrepreneur will be ready to minimize the number of failures while maximizing the learning level (Zenger, T.R., 2016). Coming to the hypothesis's formulation, yet the conjectures must comply the criteria of clearness and falsifiability: the second one criterion is particularly needed to avoid bias and other kinds of distortion, such as false positives perceptions during the decisional process. Falsifiability is defined (Eisenmann, 2013) as the possibility to be rejected if resorted to the right specifical experiments, by using an appropriate objective criterion that can quantitatively measures an apparently abstract dimension. Since the falsification counts as a kind of central moment, the test utilized should be rigorous and carefully setted, other than realized on reliable and high quality data, gathered according to precise and agreed rules; the most classic tests, usable by every type of entrepreneur and all the possible business scopes, are personal interviews, survey and poll administration, as well as A/B comparison and MVP (Minimum Viable Product). The use of MVP version empirically demonstrated huge utility, given that it allows of quickly testing different versions about the same offering, therefore avoiding preventable commitment in terms of time and financial additional resources. The Minimum Viable Product is a mindset setting, initially suited on the business background but even relevant in other contexts, seen that it provides a solid tool resulting the more useful (Ries. E., 2011) the more is the uncertainty level exhibiting in any knowledge side. During the last step, following the testing process, the entrepreneur's focus is suggested to be towards various biases: indeed, their existence's documentation in literature is widely reported in a number of scientific papers, both in psychological and socio-economic studies. They include acquiescence (i.e., distortion in data collection due to respondents which tend to give answers depending on entrepreneur beliefs rather than complying to a truthful criterion) and selection bias (Kahneman, Slovic, Tversky, 1982; Kahneman, 2011; Clark & Wiesenfeld, *Harvard Bus. Rev.*), confirmation (Gilbert, 1991) and

overconfidence (Cooper et al., 1988; Koellinger, Minniti, Schade, 2007; Klein, 2007) bias, optimism bias (Kahneman & Lovallo, 1993). The existence of biases is the more likely the less defined are the selected metrics; in his book "The Lean Startup", Eric Ries proposed a number of quantitative thresholds, usable in very diverse application fields: such numerical limits become essential when the entrepreneur comes to the decision whether proceeding with tests, abandoning the idea or finding minor changes. In case he chooses not to proceed with the same initial setting, two ways are in front of him: definitive desertion or pivot. The second one consists of re-considering the business idea and theory, in light of the conjectures' falsification or new inputs deriving from external environment. The review of his own initial convictions has to be seen as a good starting point, rather than as failure and shame; in fact, the cyclical loop generated from such thinking approach results as exactly the principle on which is based the scientific method, suggesting for an iterative process in incessant evolution and, therefore, admitting errors and re-begin points. Furthermore, the continuous mutual feedback interchange among the business protagonists aims to deal with the high uncertainty, again, controlling for the economic investment on not-added-value activities and resources, but a reliable measure of the value is not common knowledge in ex-ante scenario, so that it looks necessary initially exploring the business ecosystem with someway initial limited commitment. The unstoppable feedback exchange found its roots in the *real options* conceptualization, a widespread framework largely adopted into the finance world (McGrath, R.G., 1999; Adner, R., Levinthal, D., 2004) and similar to the decision tree, a diffused tool in project management and other scientific disciplines. These provide help in case of highly uncertain financial situations: the idea passes from being a whole project to becoming an authentic decision tree branching, where each branch represents a real option. Designing and implementing rigorous experiments allow to avoid option trap, that might hinder dropout or generate escalation and overcommitment.

Thus, the validation process conducted by the entrepreneur may be interpreted as a real option purchase of partial business idea, that is, when the experiment finishes the entrepreneur can decide to pursue the project exercising its own option, otherwise abandon the idea waiting for option expiration date. In analogy on what reported in the real options theory, the entrepreneur appears as in front of a decision node every time after an experiment conclusion: here he has to select among pivoting, pursuing, and abandoning the idea. Camuffo et all (2017) showed how a scientific method is positively correlated with amount (and extent) of entrepreneurial pivot and exit decisions. The several choice criteria are all ascribable to the one based on the perceived value of the business idea and the consequent expected profit; the term "perceived" deserves attention since it distinguishes if compared to the actual value of the idea, due to bias during the assessment or interpretation deriving from internal distortion effects or environment conditioning. Then, a further point is the influencing power of the scientific mindset on the perceived value comprehension, aimed to isolate the

disturbing variables for getting more accurate information about the expected income (i.e. without the frequent overestimation tendency). The scientific approach in decision-making routines is a recently introduced methodology, slowly diffusing nowadays among entrepreneurs and scholars; indeed, a certain number of relevant studies are moving toward this direction, and with a heterogenous geographical distribution: e.g., the Russian studies realized by Veretennikova & Vaskiv (2018) confirmed the increasing interest in such thematic at global level, while highlighting its centrality at managerial view occupied in launching new innovative products/services, namely realities characterized by largely agile and complex dynamics. However, the international literature still lacks evidences about the effectiveness brought by scientific thinking, and one of the greatest contributions comes from ICRIOS research centre of Università Bocconi in Milan. In particular, the RCT experiment conducted by Camuffo, Cordova & Gambardella (2017) investigated whether the scientific routines applied on decision-making activities had an observable effect if measured in only early-stage startups: the focus has been over the consequences come to light in terms of performance, amount of abandoned ideas and amount of pivots. The conjectures were that the application of treatments on early stage startups - where the external effects are minimum, and contingencies have yet influenced at a low level - would have resulted in 1) greater economic revenues, 2) major number of left entrepreneurial ideas and 3) greater number of pivots. This kind of study has been conducted as a Randomized & Controlled Trial, because of the necessity to be sure the effects could derive only by the causal variables, without environmental influences. In order to verify the natural differences between the participants, a monitoring program was established, including telephonic interviews with once a month frequency, aimed to detect intrinsic scientificity level at decision nodes and type of conducted activities. So, the whole pool of participants was divided into two homogeneous sub-groups through a randomization criterion, with the aim of avoiding the disturb effects introduced by internal and intrinsic heterogeneities initially in the sample. Hence, while one group experienced the scientific treatment (so named Treatment Group), the other served as controlling means (so named Control Group): by this way, when the outcomes deriving from the experiment come out, it becomes easier to understand whether the observed result belongs to one effect rather than to another, isolating the causal variables since it became doable linking the evidences to the respective diversities in treatment. A course composed of ten lessons on market analysis and feasibility testing was given to both treatment and control group, introducing the only difference that in treatment group the execution of activities in terms of scientific view is taught. In the end, the hypotheses were confirmed: the treated early-stage startups, compared to the early-stage startups belonging to control group, systematically reported superior amount of economic turnover, along with greater number of both pivoting and abandoning rates; this result confirms the starting intuitions, and underlined how a more rigorous and structured approach can lead entrepreneurs to better recognize i) the most profitable paths on which develop

the idea (pivot), ii) the most efficient means to better maximize the profit (higher revenues), and finally iii) the cases where the initial business idea is totally wrong, given the boundaries conditions.

1.3 Heuristic Search & Effectuation

Alternatively to the scientific method just illustrated, in the existing previous literature the possible solutions offered with the purpose of tackling (i.e., mitigating its effects and negative impacts) the entrepreneurial uncertainty are the heuristic search versions, and they are mainly three: effectuation (Sarasvathy, S.D., 2001), discovery driven planning (McGrath, R.G., & MacMillan, I.C., 1995) and confirmatory search (Shepherd, D.A., Haynie, J.M., McMullen, J.S., 2012). If considered the solo discovery driven planning, it is possible to distinguish a set of distinct phases to strictly follow. Indeed, McGrath & MacMillan propose five diverse items, in order: business framing (planning definition aimed to locate the best initiatives to pursue), benchmarking (referring to both market and competitors), and translation in terms of functional strategies along with focus on requirements about the operations. Yet, assumptions documentation and, finally, the phase in which we have to clearly identify the milestones. The totality of such rules provides the tools suited to restrict the impact of the assumptions, which each entrepreneur inevitably makes during the setting of its own business since, as already hinted, the building of systems born on fragile bases is a very frequent and common problem. Nevertheless, the high uncertainty degree necessarily imposes of narrowing it down by using assumptions as means, so that their utilization is fundamental and cannot be neglected; hence, the greatest objective is to let entrepreneur can really understand the huge impact brought by his assumptions on the final outcome. In particular, the first 3 phases accurately described the entrepreneurial idea also in light of the assumptions making it doable. Instead, the fourth and fifth phases act with the aim of validating the conjectures' goodness, other than measuring the possible impact of their variation on the enterprise scope. Basically, the primary goal refers to the fact that it is highly better to avoid resources commitment in case of fallacious initial ideas, and this is the more efficient way: starting by deeply investigating as in a sort of feasibility analysis, before to proceed in pursuing further investment of financial, time and human resources. Yet, Shepherd et al. (2012) propose of using the confirmatory search heuristic on every assumption, with the objective of confirming (or rejecting) its goodness. It can be conducted by resorting to three different sub-types: positive search (i.e., by testing the conjecture truthfulness when the veracity is expected) and, as opposite, the negative search (i.e., by testing the assumption goodness when the contrary is expected), other than the mixed search (i.e., by merging the previous ones). Based on such search versions, it is possible to proceed in generating several frameworks, which vary depending on a number of factors (e.g., kind of assumption, odds to underestimate its impact compared to the overrate probability, cost associated to the esteem error). All the presented procedures try to test the whole of the

uncertainty sources, in order to limit distortions due to existing biases (e.g., confirmation bias) and errors on the cost esteem linked to wrong initial assumptions.

Finally, it comes to Effectuation heuristic search: Sarasvathy (2001) describes an approach based on effectuative processes, differently from what usually used (i.e., causal ones) by both entrepreneurs and managers. Indeed, the causal method mandates to realize the means selection by beginning from a given effect: this path of course leads the risk of having a fallacious (due to the high entrepreneurial uncertainty) starting point, consequently bringing erroneous conclusions. As effective solution, she defines the effectuation standpoint as something which puts the roots into the available resources (e.g., time, cash, immobilized economic flows, real estate, human resources, network, and so on), so that consequently choses the best alternative among the possible usable business scenarios. However, this is not a linear process since is follows iterative steps: the idea development is continuously dynamic and has to be shaped according to the new information acquired throughout the venture progress. Similarly, the management approaches nowadays are quickly diffusing at several levels of the organizations (e.g., agile, scrum, complex matrix structures, elaborated cross-functional teams, etc…), proceeding along a "Bottom-Up" mindset comparable to the one traced by Sarasvathy's theory, fostering a more inclusive environment and making it able to deal with the new challenging and hyper-dynamic current competitive opportunities. In this case too, the heuristic search aims to avoid an excessive level of investment on the not-best solutions, so that the resources dispersion minimisation is made possible thanks to four primary principles (to strictly comply if the desired effect is of concentrating investment on few, precise and remunerative aspects) : 1) focus on reduced losses rather than profit maximisation; 2) preferring the strategic alliances and partnerships, rather than pursue competitive strategies based on market analysis and trend predictions; 3) focus on continuous development of expertise and, more in general, of business experience, instead of looking at the historical series and at the previous entrepreneurial experiences; 4) trying to keep control over the future and the possible event evolutions, in place of making unreliable predictions and basing the long-period tactics on conjectures about what it is impossible to experience at the moment.

The final purpose is still that of placing boundaries around the assumptions' effect, preventing the use of wrong resources, with excessive commitment at the wrong time or in the wrong place. Saras Sarasvathy (2003), in her essay named "Entrepreneurship as a science of the artificial", wrote about some key concepts by drawing on Herbert Simon's article "Sciences of the artificial". The essay wants to connect the following four ideas to recent paper on the entrepreneurial expertise:

i) the natural laws constrain, without the power of dictating the implemented designs;

ii) necessity of seizing every opportunity, in order to avoid

the use of predictions in design process;

iii) we have to accept that locality and contingency both govern the whole science of artificial;

iv) near-decomposability is a key feature of the enduring designs.

The principles Sarasvathy provides in her studies stressed the centrality of maintaining focus on flexibility, in view of the contingency dominion all over human activities. In conclusion, the entire set of relevant key factors falls into five categories: 1) *bird in hand*, namely capability of founding and developing the entrepreneurial idea putting roots into the initial personal resources owned by the decision maker, in terms of individual abilities, background and network; 2) *affordable loss*, standing for the measure in which the founder is ready to invest the maximum affordable amount looking at time as well as at financial investment; 3) *crazy quilt*, gauging the extent to which the entrepreneur succeeds in mitigating uncertainty by adopting proactive behavior (i.e., creating contact network with all the components of the business chain, like clients, suppliers and competitors); 4) *lemonade* orientation, indicates how much the founders exploited unexpected events to create new disruptive opportunities basing on the available resources and flexible aptitude; 5) *pilot plane*, when the focus is on what entrepreneur can control and does quite well, so that execution becomes a key success factor at the expense of wait and predictions.

Though, it appears equally relevant the importance of keeping in mind that such constraints represent a superable limit someway, in the sense of circumscribing the area in which startupper can move, but without defining exactly the pathway to walk; that is, a tight leeway exists and waits for being exploited.

1.4 Team heterogeneity and other effects

A really wide preexisting literature already established about topics as the influence of team heterogeneity on corporate performances. However, heterogeneous composition may refers to a number of facets, ranging from age, passing through gender and geography, until to personal behavioural traits. First of all, the trigger for a such big research flow was a series of dated essays (Resnick et al., 1991; Nonaka, 1995), asserting that fruitful discoveries in group dynamics are brought by simultaneous presence of diverse standpoints and perspectives by one side. Meanwhile by the other side, more recent works, as those proposed by Jehn et all (1997), demonstrated that team characterized by highly different education experiences had relevant more difficulties in defining activity progress, thus presented a prominent problem in the analyzed framework: heterogeneity appeared to bring, along with improvements in performance, a certain degree of difficulty into the management of internal conflicts. Van Knippenberg and Schippers (2007) defined team heterogeneity as the perceived difference in attribute features among team members. The essay of Mell Van

Knippenberg (2016) deserves to be mentioned, as he underlined how many scholars deeply contributed to the insights found on team heterogeneity, focusing on influence affecting firm's results and decision-making processes. Early explorations (Phillips, & O'Reilly, 1998) were based on social variables (e.g. gender, race, age), often leading to penalizing effects on performance and internal satisfaction. Successively, also counting on a strong Asiatic contribute on this side, a deeper research began and shifted toward less superficial heterogeneity factors: new attention was given to discern between demographic features and expertise factors, such as professional background and university achievements, which could reflect the accumulated knowledge, standpoint and ideological tendencies. Kristinsson et all (2015), drawing on information decision-making theory from perspective of cognitive resources diversification, declared that different team members consider issues from different viewpoints according to their experience, while at the same time the integration of different insights is more likely to improve disruptive creativity and team decision-making capability. Great contribute was offered by Jehn et al. (1999), which in "*Why Differences Make a Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups*" presented a study aimed to criticize prior approaches and widespread ways of thinking. They stated there are many factors leading to diametrically opposite evidences, so that was necessary a division between 1) information, 2) social classification attribute and 3) value heterogeneities; the conclusion was that the first type positively affected performance through task conflicts, while the second one had negative influence on overall performance through interpersonal conflicts. Klotz et al. (2014) proved that heterogenous compositions lead to more diverse knowledge and capabilities, thereby foster creativity and innovation. However the phenomenon encounters side effects, given that more homogeneous teams sometimes achieved better results thanks to higher cohesion, that significantly improves conflict management and efficacy (meant as speed in reaching for purpose).

Other papers published by Jehn again faced with such topics, highlighting how the team conflict was due to the perception of team members on intra-team cognitive differences and goal incompatibility. At the begin, scholars used to believe conflicts leaded to lower effectiveness, later Jehn helped to realize that task conflicts were positively correlated with resulting performance, while relationships conflicts were negatively correlated with overall efficiency. Also Fitzgerald et al. (2017) employed effort in investigating the above themes, declaring that diverse professional backgrounds and experiences produced different opinions on the same point, which was bound to improve the degree of team task conflict management. Consequently, such results suggested for correlating convergence of diverse opinions among members of different expertise with enhancing in entrepreneurial innovation and decision-making quality. This brings to a relevant conclusion: task conflict plays mediating role into the relationship between team heterogeneity and performance (i.e., the positive influence of heterogeneity affects venture outcomes through task conflict). Drawing on a very recent work of Zhang

(2019), aimed to reveal the contribute guaranteed by expertise heterogeneity (i.e., vocational and professional background) on team performances through mediating effect of team conflict, it seems to exist strong evidence of such relationship. The mediating role of team task conflict and attitudes toward heterogeneity is prominent and central.

Deserves to be cited another recent work (Hoogendoorn et al., 2017), based on a field experiment involving 573 students, where exogenous variation was ensured in (otherwise random) team composition by assigning students to various teams according to their measured abilities. Hoogendoorn demonstrated how corporate performances subtend under three macro-categories (i.e., opportunity recognition, problem solving and implementation) and thus studied their variations. They found that, within a team, a balanced combination of higher and lower cognitive abilities levels is largely more productive as some people can be assigned to mundane tasks (usually implementation) while others to the ones calling for greater cognitive capacity. Consequently, performance of teams first increases than decreases with ability dispersion, and average team ability is not related to team performance.

1.4.1 The role of network

A great current of literature has been dedicated on the argument, by treating the topic both in qualitative and more quantitative ways. Team social network definition usually focused on the existence of network based over informal - or/and formal - ties between team members and external actors of market (Adler & Kwon, 2002). Arif T. (2015) studied social networks of computer engineering department within the Indian Institute of Technology, getting quantitative insights about any behavior. Also organization theorists coming from universities in east of Europe, Lithuania in this case, invoked the social capital theory application to social network paradigm (Jurkevičienė et al., 2018). It provides theoretical evidence for links between entrepreneurial heterogeneity and performance, by answering that benefits are due to complementary in psychological traits and diverse attitudes which - when supported by right mix and overlapping - lead improvements in outcomes. Aldrich and Kim (2007) confirmed how entrepreneurship requires social connections to several professional groups, usually not accessible to a lone entrepreneur. Again, invoking literature on the social capital theory, Reagans et al. (2004) suggested the compositional diversity provides benefit thanks to the range of diverse ties that each member guarantees externally to the team environment, so obtaining access to valuable extra resources and information.

A deeply large-scale Russian study carried out by Aven and Hillmann (2018), by analysing 9461 entrepreneurs and 2446 industrial enterprises, showed that variation among team members' brokering ability significantly predicted the starting capital gained by the firms. The focus was on team members' ability to act as network brokers. Furthermore, another evidence was that when both average and variance in brokering potential were high for the team, then firms raised greater starting capital. A

recent paper published by Butler et al. (2019) put attention on new tendencies: with the increasing penetration of digital paradigms into the entrepreneurial competition, the traditional need for proximity to specific locations or the necessity of huge funding for infrastructure building has diminished, and of course such effect has been recently exacerbated by pandemic emergency. Thus, nowadays entrepreneurs pursue locations that provide more opportunities for founding rounds and greater social networks. So, Butler and colleagues grasped data from CrunchBase and PricewaterhouseCoopers, while intercepting network dimensions by scanning social pages from LinkedIn. The results coming from 1418 analysed entrepreneurs suggested that funding rounds per year is a reliable indicator playing significant and positive role in affecting startup creation in certain locations: local social network density generates stickiness to the local environment, thus negatively influencing entrepreneurs' willingness to relocate towards further places. There was also evidence that midcareer individuals (like millennials) are more likely than early-career and late-career to create successful technology startups. A new work carried out by Geremias, Lopes and Soares (2020) on a sample of 480 undergraduate students gives evidence of the positive correlation between network centrality and internal learning in young teams. Such result allows to understand the importance of centrality in advise networks among innovative teams: this suggests for positive correlation between such centrality (e.g. it can be measured by the Team Building variable tracked in IVL dataset) and scientific approach, since the latter is based on team learning activities. The effect could be observed through the influence of team composition, given that the Geremias' study was conducted on only-students groups.

1.4.2 Psychological dimensions

A certain amount of Asian papers (Su-li & Ke-fan, 2011) conducted extremely quantitative researches on abstract topics, for example by adopting the MBTI framework to interpret risk decision-making activities within group scope. A set of variables described individual behavior differences: (E)xtraversion vs (I)ntroversion as source of spiritual vigour, (S)ensing vs i(N)tuition as ways to grasp information, (T)hinking and (F)eeling in decision-making attitudes, finally (J)udging and (P)erceiving in adapting to external contingencies. The relevant results were that:

1. teams with majority of J members were more prone to make optimistic estimates about entrepreneurial opportunities than S majorities;

2. groups with more P individuals were likely to detect greater amount of opportunities and lower risks, while possessing higher risk perception if compared to those with J majority;

3. teams with more E members felt lower risks than who was labelled as I type.

The resulting outcomes helped to understand how it should be of central importance to know and interpret personality traits, thereby prevent too optimistic (or pessimistic) judgements and false negatives/positives through a rational decision-making process. The already mentioned studies produced by Clark and Wiesenfeld (2017) focused on personal traits by the bias viewpoint: they reported cases of companies which made strategic decisions based on biased samples, that are more likely to corroborate initial hypotheses even if data suggest the opposite.

Other scholars (e.g. Parker, S.C., 2006) stated that entrepreneurs differ in the way which they anchor to their own beliefs, leading to ignore external signals and information coming from real market, with such phenomenon more pronounced in older individuals. Then it means less adaptivity in decision-making. Difference in age also suggests for using seniority parameter to control variations in natural scientific degree, given that scientific method is exactly based on better interpreting external signals. Several types of biases usually affect the human decision-making process, and they are subtended to certain psychological and attitudinal aspects, even if a scientific approach setting is adopted. York et al. (2014) revealed them in a dedicated paper: acquiescence, selection, confirmation (also described into Gilbert's essay published in 1991), overconfidence and optimism biases were the most frequent and harmful. Again in terms of age, the work of Amit et al. (2001) gave contribute. Firstly, they found that entrepreneurs engaged in business planning activity reduced the likelihood of venture disbanding while increasing the odds of pursuing on the idea with success (so business plan boolean variable is used as control). Secondly, they demonstrated younger entrepreneurs showed more overconfidence bias while running ventures, along with lower decision comprehensiveness - similarly to what written by Parker (2006) who showed how older entrepreneurs were more anchored to their own prior beliefs, given the major amount of prior experience, lacking in capacity of reacting to market signals and evolving information. This current suggests for the use of seniority dimension as control variable in regressions, since it can be the effect through which is mediated the scientific approach.

Further findings on personal traits of entrepreneurs (Shah & Tripsas, 2007; Shah & Tripsas, 2012) took into consideration the possibility that entrepreneur is even the user of the product he offers on market: in those papers is proposed the idea of a sort of correlation between personal motivations and outcomes. How in these cases do entrepreneurs exploit opportunities (key aspect of effectuative approach) based on initial inventions thought for their own use? Do the social capital (e.g. involvement in user communities, contacts to markets) weight increase or decrease within these scenarios? The most interesting emerging question is: does such process depend on nature of the community problem? That means, for instance, the 'inventors-users' in medical sector can be more prone to

share their discovers given the prominent social impact, maybe emphasizing the economic gain less at the expense of higher interest for fighting others' sufferance. Wang et al. (2019) tried to connect psychological capital with startup performance, basing on reliable interviews registered by famous international entrepreneurs: the resulting finding was that human (i.e. age and education, work experience, near relatives models), as well as relational (i.e. trustworthiness and relationships among co-founders) and strictly psychological (i.e. optimism, autonomy, hope, resilience) key features showed being crucial for born, development and performance of new ventures. The central relevance of the psychological capital has been recently underlined by Alessandri et al. (2018) too, who created structural equation modelling analysis and found that absolute levels as well as increases in PsyCap (hope, autonomy, resilience, optimism) predicted work engagement increases, which in turn predicted better job performances.

Finally, a narrow set of specific variables has been adopted according to what described by St-Jean and Tremblay (2020), who declared how mentors' support can facilitate the development of a particular psychological trait (i.e. the opportunity recognition subtended to self-efficacy) through the moderating effect of psychological aptitudes, mostly the Learning Goal Orientation (LGO). Such last property has been computed as arithmetic mean of 5 different sub-variables tracked thanks to the following questions: i) *I tend to face with challenging working tasks which can teach me a lot*, ii) *I continuously search for opportunities useful to develop new capabilities and knowledge*, iii) *I like difficult lavorative tasks by which I can develop new competences*, iv) *The possibility to can develop work abilities is so important to take a risk*, v) *I prefer to work in situations calling for high capability and talent*. What emerged was that mentoring supported increase in opportunity recognition only for low LGO mentees.

1.4.3 Industry effect

Mitchell and Shepherd (2010) explored whether the environment in which entrepreneur plays might change his decision-making criteria, discovering that the executives acting in more dynamic sectors, namely characterized by high uncertainty in future predictions (e.g., innovative startups), are prone to take decisions inconsistent with market and harmful for corporate performances. This result makes think that more dynamic, uncertain and then risky industries (e.g., ICT) can lead to a minor average degree of scientificity.

Anna et all (2000), looking at a sample coming from US states of Utah and Illinois, investigated whether relevant differences in nature of industry mitigated the gender effect. According to the SBA, 22 million of US small businesses generated more than half of the total GDP and were the principal sources of new jobs. The National Foundation for Women Business Owners reported that the amount of women-owned ventures experienced huge growth during the last fifty years. Although the growth in quantity is encouraging, the size remains small in terms of revenues and employees if compared to male-owned firms. One explanation for the disparity is that

females tend to concentrate on retail and service industries, where markets are smaller in opposition to sectors like high-technology, construction and manufacturing. One of the most fruitful streams of research based on the self-efficacy trait. The final outcomes showed how traditional-women business owners had largely different key success factors than non-traditional owners; the resulting conclusion appears to be appropriate for being extended at men level, keeping the same differences among different industries.

1.4.4 Gender effect

A largely explored current exists on differences in gender in terms of decision-making aptitudes. Please note that literature elaborated in this sense is not aimed to state the supremacy of one category rather than the another; instead, it aims to take notice of the existing differences, due to endogenous, evolutive and natural factors, thereby formulate the perfect mix in team composition and diversities management. However, the gender effect may be mitigated by the dimension named female identity, as highlighted by Shepherd (2012). Apesteguia (2012) carried out a complex and long field experiment, demonstrating that: i) teams formed by women totality are significantly outperformed by all the other gender combinations, both at undergraduate and MBA levels; ii) the best performing group is two men more 1 women for MBA classes (suggesting for a mitigating role of women presence); iii) the differences in performance are explained by those in decision making and personal traits, indeed women-unanimity teams were less aggressive in pricing strategies, invested less in R&D but more in social sustainability. A more dated work of Gatewood et al. (1995) explored differences in gender about motivations meant as success key factors in technological entrepreneurship – then concluding that women who started having personal reasons (e.g. autonomy) and men who started having external incentives (e.g. solve a perceived market need) were statistically more likely to successfully terminate the initial phase of firm development. Shepherd (2012) also affirmed that gender effect can vary depending on the nature of industry (e.g., traditional or non-traditional) in which entrepreneur plays, so suggesting that gender impact can be controlled, for example, even through the kind of offering. Still, Shepherd invokes more attention on conditions under which gender differences are magnified (e.g. non-traditional-for-women industries), thereby recognize and fight them. Finally, he concludes that the focus could move from the amount to the nature of the experience (e.g. failed attempts of startup establishing), thus leading to consider such aspect as control variable throughout the regressions.

Findings in anxiety management (De Visser et al., 2010) confirmed relevant differences in genders: by a medical point of view, decision-making and anxiety share underlying neural substrates, so that variations in anxiety handling capability provoke variations in decision-making and cognitive functioning. Indeed, women were demonstrated to be more able in anxiety management, resulting in higher lucidity through complex decision

moments. In addition, the anxiety impact was more evident for men during the early stage (i.e. exploration phase), whereas stronger on women during the exploitation phases of the tasks. A key role is played by the perfectionism trait, strictly linked to fear for failure and anxiety generation (Frost, Marten & Lahart, 1990). Masson, Cadot and Ansseau (2003) used a sample composed of 617 first year students from Liege university to track potential differences in gender and experience of failure (i.e., repeating an academic year): the outcome said that girls were more subjected to society exigencies of studying and consequent major sense of anxiety and incompetence, while boys reported higher scores in self-confidence but even higher tendency to procrastinate, because failure expectancies could be deeply harmful for their self-esteem. These findings explained why the rate of male dropouts after the first academic year was superior, also justifying the female superior in terms of performances at university. In the same way, males were more likely to declare as first choice of studies something near to short and less difficult paths. Another quite recent paper (Kluen et al., 2017) suggests that gender differences in anxiety management affect risky decision-making situations: acute anxiety escalates cortisol activity, which stresses the risk attitude in men but not in women, thus driving to diverse behaviors under pressure. Also Van den Bos et al. (2012) underlined differences between men and women toward risk appetite, stating that women were more sensitive to occasional losses and, as consequence, needed more time before reaching the same level of performance if compared to men. Stanton et al. (2010) tried to justify such differences in risk taking by invoking hormonal components, namely the endogenous level of testosterone: they discovered that high testosterone levels were correlated with greater risk-taking attitude, and this was true both in men and women individuals. The difference in taking risky choices is demonstrated even at neuroscientific level: an extremely recent study of Wu et al. (2020) observed higher sensitivity to risk and betrayal in women, by exploiting magnetic resonance imaging to investigate neural signatures. The results illustrated in neuroimaging are consistent with the previously analyzed theory. Similar findings are provided at medical level by Orsini et al. (2016), who gave explanation of such differences drawing on instinctual reasons, thanks to the evidence emerging from an experiment on rats' behavior. The registered effect was not due to differences in shock reactivity, body weight or estrous phase, so that the effect of interest was well isolated from exogenous influences. A revolutionary work is proposed by Carr and Steele (2010), who provided the first evidence that decision-making process can be affected by concerns about stereotypes and identity devaluation. Indeed, rather than attribute gender differences to innate and stable factors (e.g. biological and hormonal reasons), they discovered that women subjected to stereotype threat in academic/business settings were more loss averse (i.e. less risk taker behavior) than both men and women not facing the threat of been judged in light of negative prejudices. Instead, no gender differences in risk appetite were found in absence of stereotype threat.

Yet, a recent paper (Lee, Ashton, 2020) analyzes a wide sample of 347.192 persons

from 48 different countries to conclude that women averaged higher than men in specific psychological features, such as emotionality and honesty/humility. This insight suggests gender as control variable into the psychological influence of personal traits. Stoet et al. (2013) detected differences in gender about multi-tasking activities: men suffer more when there is necessity of handling multiple commitments; however, the academics underlined the lack of empirical studies on gender differences in multitasking, so advising for caution against making generalisations.

Zhao and Zhang (2016) focused on an interesting point: they found that people tend to trust strangers of opposite gender more than those of same gender, and females trust females much more than males trust males. This key finding can suggest that male teams (absolute absence of females to mitigate contrasts) suffer more during the coordination phase, and it can be more relevant in view of the scientific method, in which orchestrating the feedback exchange activity is a core issue. Block et al. (2018) found that young boys endorsed communal values less and agentic values more than girls, suggesting that gender differences in core values emerge early in personal development and predict children's expectations, even without receiving the influence from external environment and society rules; it drives to consider gender control as crucial when analyzing patterns in psychological traits. Finally, looking at venture capital world and corporate reliability, Tinkler et al. (2016) adopted an experimental design to investigate venture capitalists' funding decisions (VCs) in high-growth and high-tech entrepreneurship. They found that entrepreneurs' technical background moderated the gender effect, and women received higher evaluation by the venture capitalist when the assessment moment happened with close contact. When in presence of technical background of both male and female entrepreneurs, the VC evaluation did not register variations among genders; anyway, in situations where technical background was absent and prior performance information was ambiguous, the female entrepreneurs received lower evaluations than male non-technical entrepreneurs, meaning that women were supposed to be less competent and having less leadership ability when available information was insufficient.

1.4.5 Academic level and background effect

An interesting recent randomized field experiment conducted by Chatterji et al. (2019) has investigated the advice effect: the sample was a pool of 100 Indian high-growth technology firms, whose founders received advice from other entrepreneurs about people management. The entrepreneurs who received advice built on formal approach (i.e. regular meetings, consistent goals, frequent feedback exchange) grew more and were less likely to fail; in addition, they found that entrepreneurs with MBA, accelerator experience and similar, did not follow the general pattern, suggesting that formal training limited the spread of peers' advice. Such result can be extended since scientific method put its own roots into the capacity of listening and observing

feedback from environment and market - and it looks like academic level and previous professional experience can weaken this capability - so that they might become useful as control variables during the regression analysis. Furthermore, Miozzo and Di Vito (2016) demonstrated that entrepreneurs having more scientific education, when the business idea was launched into the market, faced difficulty in cognitive distance respect to their customers, other than suffering for lack of management practices knowledge. This implies that background differences can affect the ways of firm conduction. Yet, the website *faculty.washington.edu* reports an article of Greenwald and Banaji (1995), observing how different types of cultural and national heritage, as well as the kind of university background, affect the decision-making process since entrepreneurs experience implicit differences, coming from diverse moral values, natural creativity and motivations. It is of interest to notice that, according to Toma's (2020) results, along some dimensions (i.e. revenue, dropout) the condition of STEM-majority team followed the same pattern tracked by the network variables (advice from accelerator and incubator), implying how startups having STEM majority in composition required for greater support on business side offered by incubators and accelerators.

1.4.6 Prior experiences weight

As declared by Vliamos and Tzeremes (2012), the teams having previous experience in the same sector can count on contacts network, facilitating development and firm growth. After, an entrepreneur with prior experience in tasks regarding the same industry is able to better identify opportunities and holds more odds of finding market gap. Also the researches of Pugliese et al. (2016) confirmed that startups having more expert teams (referring to a specific industry) are prone to experiment higher odds of success. These beliefs are confirmed by several studies presented in literature (Gimeno et al., 1994; Tornikoski, 2007; Preisendorfer et al., 2012; Cassar, 2014), since the accumulated experience is a discriminant highly difficult to replicate, and allows entrepreneurs to understand competitive structure and market strengths, other than quality standards and the more profitable trends. Moreover, it improves the capability of accurately estimating revenues and costs and therefore performing more precise predictions, a useful outcome that diminishes the usually observed effects of discouragement and delusion emerging after the initial instants. Fern et al. (2012) discovered that entrepreneurs tend to overly rely on their own historical industry experiences, when shaping initial corporate strategies; anyway, those with more different experiences showed less pronounced bias and this is why an artificial variable (i.e. number of industries in which experience is cultivated) has been taken into consideration. Looking at team level, further facets are worthy to be considered: influence of the offering type (Schleimer and Shulman, 2011), maybe due to products' physical nature (design and creation phases) which suggests for higher scientificity values, and abstract/flexible nature of services suggesting for higher effectuative score.

Finally, there are the group decision-making rules, since Kaplan and Miller (1987) concluded that into no-information condition, decisions under majority and unanimity rule did not differ, whereas in complete-information condition the unanimous decisions fell farther to the right, namely closer to the position of the most extreme member.

1.4.7 Stevens' scales Theory

According to the theoretical basis provided by Stanley Smith Stevens (1946), it is mandatory to consider the kind of scale on which the numbers are expressed. Indeed, this thesis project used data and numerical values deriving from personal judgements, since they come from entrepreneurs' auto-assessments and esteems made by the research assistants, so that they might be subjected to biases and distortions. This aspect is captured by the measurement scales theory, which provides some properties and conditions to better interpret any type of quantitative characteristic, taking onto consideration both its limits and reliability. Referring to the data of interest in this study, they are mainly measured on a particular kind of system: the ordinal scale. Such is due to the fact that the totality of values considered for analytical manipulation came from subjective perceptions, so that the unique possible level of expression is only at the second degree of 'nobility', meaning it supports just for two types of relationship: non-equivalence and ordering, where the first is in common with nominal scales (i.e. those utilized for categories such as names and gender, or Mohs hardness, air quality), while the latter characterizes the scale's qualitative nature. As displayed in Appendix A, in which a table extracted by Franceschini et al. (2019) can be analysed, the ordinal scale refuses consistency in distances (intervals) and ratios, a limitation due to its low nobility degree. In fact, although the low level, such scale accepts a number of transformations: starting from the most refined scale, we view similarity, exponents, linear function (e.g. translation, max-min normalization), increasing monotonic function (e.g. statistic cumulate transformation) and permutation, respectively introduced into the scales of ratio, logarithmic interval, linear interval, ordinal and nominal. It can be demonstrated the transformations feasibility on ordinal scale, given the following enunciation: $y > x$, where for instance x assumes value 4 while y assumes value 7, easily becoming $7 > 4$.

Similarity (by assuming for example α=5):

$$\varphi(y) > \varphi(x)$$

$$\alpha \cdot y > \alpha \cdot x$$

$35 > 20 \rightarrow$ thus accepted.

Linear transformation (γ=6; δ=10):

$$\mu(y) > \mu(x)$$

$$\gamma \cdot y + \delta > \gamma \cdot x + \delta$$

$52 > 34 \rightarrow$ thus accepted.

Increasing monotonic function (e.g. cubical power):

$$y^3 > x^3$$

$343 > 64 \rightarrow$ thus accepted.

Permutation (items inversion):

$$y \leftrightarrow x$$

$$7 \leftrightarrow 4$$

$$4 > 7 \rightarrow \text{thus refused.}$$

In conclusion, an ordinal scale has a restricted set of available indicators used for centrality: just modal and median values, whereas any kind of average (arithmetic, weighted, harmonic, geometric) is forbidden. A similar behavior is followed by indicators of dispersion: the logarithm of number of classes along with fractiles are permitted, but variance and percentual variation are not reliable on this scale. Finally, statistics as chi-squared and verse tests are doable, while t-student and f-fisher forbidden; Spearman correlation exists on ordinal scale, instead the Pearson correlation coefficient is not computable. Please note that through statistical analysis and regressions, such forbidden operations (e.g. variance computation, average, and so on) are however applied to the dataset, even if not completely corrected by a theoretical standpoint. Although the boundaries surrounding the use of the ordinal data gathered within the experiment of interest, the goodness of the manipulations is however high, given the professionality and experience of who assigned evaluations (namely the research team), able to guarantee good reliability in assessments and increasing with the passing of time - thanks to learning economies, evolving mastery of the arguments and standardized tasks repetitively executed. In other words, the strong assumption concerns the fact that each research assistant has been able to assess intervals between values by using steady criterion, while valuating the ranking to be used; that is, for instance considering the difference between 4 and 5 equal to the one perceived between the ordinal values of 2 and 3. As cited by Gioia et al. (2013), the qualitative research has been critiqued as too often lacking in scholarly rigor, so that the authors answered by confirming the richness and potential for discovery of such approach, indeed proposing a systematic summary and grounding theory articulation in order to bring qualitative rigor while presenting inductive research. Also Bloem (2018) discussed about validity of cardinal treatment on ordinal variables, asserting how robustness depends on the specific details of individual specifications, since it deeply varies from a statistical setting to another.

1.4.8 Blau's index

As explained into the previous paragraphs, the indicator proposed by Blau is utilized in this work, since it has been adopted in a number of eminent papers and researches, other than analyzed and adapted in several dissertations (e.g., Herfindahl, 1950). It is useful in order to simply detect the diversity, namely heterogeneity, along a wide range of diverse variables. It can be defined as:

$$BI = 1 - \sum_{i=1}^{N} p_i^2$$

where p_i indicates the proportion, expressed as percentage, of a certain type of the category compared to the total numerosity, so that the ones' complement returns the extent to which each single component shows distance respect to the others, in other words the dispersion of a certain property among group members.

The Blau's indicator reminds of the Herfindahl index, used by designers of antitrust policy toward mergers in role of statistical indicator, indicating whether a merger should be challenged or not, seen the increase in market power during the M&A processes. Both the indexes aim to quantify the entropy within a system looking at variability in the components, even if in different scopes of study.

Thereby the Blau's indicator is included in regressions proposed at the end of this thesis project, and referred to a series of variables: diversity in team gender, seniority* , geographical origin*, maximum academic level achieved, academic level of the current studies, presence of other commitments, quality of student member, academic background*, prior experiences as startupper and in business plan writing. As suggested in literature, the aggregated Blau index has to be defined as sum of the sub-indicators rather than arithmetic mean, so that its formula has been expressed in the following manner:

$$\text{Aggregated BI} = \sum_i^C \text{BI}_i \qquad \in [0,C]$$

where C is the number of different Blau indicators, so as to have the value equal to C representing the superior limit of the overall index domain.

1.4.9 Research questions

By resuming the previous considerations, the research questions presented in this paragraph will be examined throughout the thesis project. First of all, the studies of Jehn et al. (1997) underlined the side effects brought by diversity in education: it appeared to lead a certain degree of difficulty in internal conflicts management, even if coupled with performance improvement. Such ambiguity is reported by a number of authors (Resnick et al., 1991; Nonaka, 1995; Phillips & O'Reilly, 1998; Kristinsson et al., 2015), who mentioned as core issue the presence of a dual effect: diverse viewpoints and insights integration imply more disruptive creativity and better decision-making outcomes, meanwhile social and moral heterogeneities are causes of negative influence through interpersonal conflicts.

In other words, only the diversity at "information level" positively affects the performance and is due to task conflicts. Yet, other scholars (Klotz et al., 2014; Fitzgerald et al., 2017; Zhang, 2019) claimed how opposite effects are likely to be observed, seen the creativity creation leading benefits along with more difficult conflict management: the innate team cohesion can be represented by the artificial variable called Internal Network, measuring the degree at which the team members have connections preexisting among them thanks to previous experience, both at work and academic levels. An interesting point is highlighted by Hoogendoorn et al. (2017), since they found that a balanced combination of

* *These are all clustered variables, with the aim of generating homogeneous sub-groups, and comparable in terms of numerosity*

higher and lower cognitive abilities levels (e.g. diversity in academic level) is largely more productive. The reason is that some people can be assigned to mundane tasks (e.g. implementation) while others to the ones calling for greater cognitive capacity; consequently, they concluded that performance of teams first increases then decreases with ability dispersion, and average team ability is not related to team performance. Thus, the first research question aims to investigate whether the several Blau's indicators, if separately considered, are statistically correlated with variations in scientific and effectuative decision-making innate degree, with such effect controlled by variables incorporating interpersonal conflicts management, such as Internal Network and experience proxy (i.e. age, previous work activities, years of experience in practical tasks).

Again, Geremias et al. (2020) recorded positive correlation between advise network centrality and internal learning in young teams; Jurkevičienė et al. (2018) invoked the social capital theory application to social network paradigm, providing theoretical evidence for ties between entrepreneurial heterogeneity and performance, since benefits are due to complementary in psychological traits when supported by right mix and overlapping. The connections importance is reported also into other works (Aldrich and Kim, 2007; Reagans et al., 2004; Arif, 2015), who linked it to a superior capacity of getting relevant results by exploiting external knowledge and network economies, as well as the possibility of obtaining access to valuable extra resources and information. Another way to look at network centrality is offered by the recent papers of Aven (2018) and Butler (2019): the first one, by analysing 9461 entrepreneurs and 2446 industrial enterprises, showed that variation among team members' brokering ability significantly predicted the starting capital gained by the firms; further, when both average and variance in brokering potential were high for each team, then firms raised greater starting capital; therefore it seems that diversity in network ability predicts credibility in front of investors. Instead, Butler (by analyzing data from CrunchBase and PWC, while intercepting network dimensions by scanning social pages from LinkedIn) discovered that funding rounds per year is a reliable indicator playing significant and positive role in affecting startup creation in certain locations, since local social network density generates stickiness to the local environment; secondly, he found that midcareer individuals (e.g. millennials) are more likely than early-career and late-career to create successful technology startups, suggesting for the Age dimension to be used as control variable. To sum up, the second point is about observing the effect on scientificity and effectuation by using variables controlling for network capability, such as heterogeneities in seniority, students' presence, academic level and background, as well as team numerosity and psychological capital traits, mostly the Internal Network and Team Building dimensions. Please note that the LinkedIn contacts counting (already proposed in recent studies) should be biased in this experiment seen the nature of participants, mostly young and with few professional experience, and this the reason why it has been completely neglected as proxy of external ties.

Looking with a focus on psychological traits, Su-li and Ke-fan (2011) - by adopting the MBTI* framework - stated that, in terms of majority within the team, 1) J were more prone to make optimistic estimates about entrepreneurial opportunities than S; 2) P were likely to detect greater amount of opportunities and lower risks than J; 3) E felt lower risks than I. Therefore effectuative people see more opportunities and less risks, so that it can be controlled by the Risk Appetite variable into the experiment subject of interest in this thesis project. Clark and Wiesenfeld (2017) reported cases of companies which made strategic decisions based on biased samples, more likely to corroborate initial hypotheses, so that it looks like such aspects could be included in a set of psychological dimensions such as Self Esteem and Novelty. York et al. (2014) mentioned how acquiescence, selection, confirmation (also described into Gilbert's essay published in 1991), overconfidence and optimism biases were the most frequent and relevant ones, and these biases can be tracked through the use of the PsyCap variables considered within this experiment. Amit et al. (2001) further explained that the entrepreneurs engaged in business planning reduced the likelihood of venture disbanding while increasing the odds of pursuing the idea with success, suggesting for looking at BP experience effect on decision-making. Secondly, they demonstrated that younger entrepreneurs showed more overconfidence bias with lower decision comprehensiveness, so the effect should be observed through age control and psychological traits. Parker (2006) affirmed entrepreneurs differ in the way which they anchor to their own beliefs, with such phenomenon more pronounced in older individuals, thus it suggests for using seniority parameter to control variations in natural scientific degree (given that scientific method is exactly based on better interpreting external signals). Shah and Tripsas (2007, 2012) took into consideration the possibility that entrepreneur is even the user of product he offers on market, so they proposed the idea of correlation between personal motivations and outcome. Wang (2019) asserted how human (i.e. age and education, work experience, near relatives models), relational (i.e. trustworthiness and relationships among co-founders) and strictly psychological (i.e. optimism, autonomy, hope, resilience) variables showed crucial for performance. Finally Alessandri et all (2018) in their recent studies concluded that absolute levels as well as increases in PsyCap (hope, autonomy, resilience, optimism) predicted work engagement increases, which in turn predicted better job performances; this suggests for psychological variables seen through commitment level control. To sum up, the third research question investigates whether a correlation makes sense between decision-making approach (natural degrees of effectuation and scientificity) and psychological capital, if controlled by experience in business planning, age, initial motivations, industry and commitment level.

Mitchell and Shepherd (2010) found that executives acting in more dynamic sectors are more prone to take decisions inconsistent with market and harmful for corporate performances, so concluding

**(E)xtraversion vs (I)ntroversion as source of spiritual vigour, (S)ensing vs i(N)tuition as ways to grasp information, (T)hinking and (F)eeling in decision-making attitudes, (J)udging and (P)erceiving in adapting to external contingencies*

that more dynamic and then risky industries (e.g., ICT) can lead to minor scientificity and in general to less efficient decision-making processes. Schleimer and Shulman (2011) cited that products are more profitable and its physical nature (design and creation phases) could suggest for higher scientificity, while abstract nature of services and flexibility suggest for high effectuative aptitude. Anna et al. (2000), in their studies looking at only-female ventures coming from US states of Utah and Illinois, found that the size remains small in terms of revenues and employees if compared to male-owned firms, as females tend to concentrate on retail and service industries (where markets are smaller in opposition to high technology, construction and manufacturing), so that gender factor could control for sector. Secondly, traditional women business owners had largely different key success factors than non-traditional business owners: the resulting conclusion appears to be appropriate for being extended at men level, keeping same differences among different industries. The fourth research question aims to investigate whether the industry to which the startup belongs can affect effectuative and scientific natural aptitude, and this relationship could be controlled through gender and kind of the offering.

An extremely recent work by Toma (2020) concluded that startups having STEM majority in composition required for greater support on business side (e.g. offered by incubators and accelerators), thus the STEM majority boolean variable could be an appropriate factor to consider as discriminant in order to detect significant differences in decision-making process and business development activities. In addition, as reported on the website faculty.washington.edu, Greenwald and Banaji (1995) discovered that different types of cultural and national heritage, and above all the kind of university background, affect the decision-making through the influence of diverse moral values, natural creativity and motivations; such leads to think that geography and academic background influence decision-making through initial motivations. Miozzo and Di Vito (2016) affirmed that entrepreneurs having more scientific education, when the business idea was launched into the market, faced difficulty in cognitive distance respect to their customers, other than suffering for lack of management practices knowledge: background differences can affect the ways of firm conduction, so as to influence the natural aptitudes in decision-making. Chatterji et al. (2019) studied 100 tech firms, whose founders received advice from other entrepreneurs about people management; who received advice built on formal approach (i.e. regular meetings, consistent goals, frequent feedback exchange) grew more and were less likely to fail; after, they found that entrepreneurs with MBA (or accelerators or similar) did not follow general pattern (i.e. formal training limited the spread of peers' advice). Such result can be extended since scientific method put its own roots onto the capacity of observing feedback from environment, so it appears that excessively high academic level and previous professional experience can weaken this capability. Finally the fifth research question investigates whether the type of background (boolean variables about majority of STEM, Economics and Other) and the academic level correlate

with the natural levels of scientificity and effectuation, when controlled by geographical origin, initial motivations and prior professional experiences (Chatterji et al., 2019).

Yet, Vliamos and Tzeremes (2012) got evidence that teams having previous experience in the same sector can count on contacts network, so facilitating the business development: team's prior experience affects decision-making through network (e.g. controlled by age). After, they found that entrepreneurs with prior experience regarding the same industry better identify opportunities, therefore prior experience into the same sector in this experiment is expected to affect effectuative approach as based on opportunity recognition and exploitation. Pugliese et al. (2016) reported how startups having more expert teams (referring to a specific industry) are prone to experiment higher odds of success, so it is possible to conclude that experiences predict success through startup sector. Furthermore, Fern et all (2012) in their researches affirmed that entrepreneurs tend to overly rely on their own historical industry experiences; anyway those with more different experiences showed less pronounced bias: this is the reason why the artificial variable described as number of industries (in which experience is cultivated) should well predict anti-overconfidence aptitude. In addition, a number of authors (Gimeno et al., 1994; Tornikoski, 2007; Preisendorfer et al., 2012; Cassar, 2014) underlined how accumulated experience is difficult to replicate, and allows entrepreneurs to understand competitive structure and market strengths, quality standards and most profitable trends; it improves capability of performing more precise predictions, diminishing the usually observed effects of discouragement emerging after the initial instants, so that we expect experience influences decision-making thanks to a better comprehension of the issue. The sixth research question is about the possible correlation between previous experience and natural levels of scientificity and effectuative mindset through a set of controls such as seniority, startup sector, number of sectors (Fern et al., 2012) and innate overconfidence. Please note that the prior experiences are measured through the use of the following dimensions: years of past experience, experience in same industry, experience as executive, the already having been startupper, the number of prior companies established, experience in business plan writing, economics and management courses attended, entrepreneurship courses taken, vertical and horizontal competencies (or aptitudes) acquired according to the experiences cultivated into work and academic world.

The last point touches the gender bias. Masson et al. (2003) assessed a large set of students, discovering that girls were more subjected to society exigencies of studying and consequent major sense of anxiety and incompetence, while boys reported higher scores in self-confidence but even higher tendency to procrastinate as failure expectancies could be deeply harmful for their self-esteem: this leads to consider the PsyCap effect as controlled by gender. Such evidence further explained why the rate of male dropouts after the first academic year was superior, also justifying the female superior in terms of performances at university. Yet, males were more likely to declare as first choice

of studies something near to short and less difficult paths, and such factor might contribute to gender differences in academic level (male one should be inferior). Shepherd (2012) stated that gender effect can vary depending on nature of industry (e.g., traditional or non-traditional) in which entrepreneur plays, thus the gender impact is controlled through the kind of offering and startup industry. He invoked more attention on conditions under which gender differences are magnified, namely looking at women in non-traditional-for-women industries; finally he asked for moving focus from the amount to the nature of the experience (e.g. failed attempts of startup establishing), so confirmed the utility of considering previous established enterprises as control variable. Gatewood et al. (1995) obtained evidence that women who started having personal reasons (e.g. autonomy) and men who started having external incentives (e.g. solve a perceived market need) were statistically more likely to successfully terminate the initial phase of firm development: it can be useful to investigate whether initial motivation drives to different outcomes through gender control. Lee and Ashton (2020) analyzed a wide sample of 347192 persons from 48 different countries to conclude that women averaged higher than men in specific psychological features (e.g. emotionality and honesty/humility), suggesting for gender as control variable into psychological influence of personal traits. De Visser et all (2010) offered evidence by a medical point of view: decision-making and anxiety share underlying neural substrates, so that variations in anxiety handling capability provoke variations in decision-making and cognitive functioning; indeed, women were demonstrated to be more able in anxiety management, resulting in higher lucidity through complex decision moments, and this could justifies gender differences in PsyCap. In addition, the anxiety impact was more evident for men during early stage (i.e. exploration phase), whereas stronger on women during the exploitation phases of tasks; such maybe could result in worse men scientific performance while worse women effectuative performance. Frost, Marten and Lahart (1990) asserted that a key role is played by the perfectionism trait, strictly linked to fear of failure and anxiety generation, so they further proved in medical terms the magnitude of some gender differences. Wu et al. (2020) registered higher sensitivity to risk and betrayal in women, by exploiting magnetic resonance imaging to investigate neural signatures: they provided proven difference demonstrated at neuroscientific level by such extremely recent study, suggesting for particular attention on the Risk Appetite variable. Orsini et al. (2016) found similar findings by medical standpoint: they explained gender differences drawing on instinctual reasons, thanks to the evidence emerging from an experiment on rats' behavior, where the registered effect was not due to differences in shock reactivity, body weight or estrous phase, so that the effect of interest was well isolated from exogenous influences. This confirmed that gender difference in Risk Appetite are explained at instinctual level too. Carr and Steele (2010), in contrast to a great amount of scholars, sustained that women subjected to stereotype threat in academic/business settings were more loss averse (i.e. less risk taker behavior) than both men and women not facing the

threat, while no gender differences in risk appetite were found in absence of stereotype threat. This revolutionary paper provided the first evidence that decision-making process can be affected by concerns about stereotypes and identity devaluation, rather than attribute gender differences to innate and stable factors (e.g. biological and hormonal reasons). Apesteguia (2012) instead offered a series of findings:

i) teams formed by women totality are significantly outperformed by all the other gender combinations, letting to interpret that women-unanimity teams are maybe less focused on mere economic outcomes
ii) the best performing group is two men more 1 women for MBA classes, perhaps due to the mitigating role of women presence
iii) women-unanimity teams were less aggressive in pricing strategies, invested less in R&D but more in social sustainability, so that differences in performance could be explained by those in decision-making and personal traits (e.g. initial motivations and startup industry).

Stoet (2013) found that men suffer more when there is necessity of handling multiple commitments, however he underlined the lack of empirical studies on gender differences in multitasking, so advising for caution against generalisations – this creates room to investigate gender difference in multi-tasking management, maybe relevant into the effectuation paradigm as based on flexibility (whereas scientific approach follows a more linear scheme). As opposite to Carr and Steele (2010), Block et all (2018) gathered evidence that young boys endorsed communal values less and agentic values more than girls, suggesting that gender differences in core values emerge early in personal development and predict children's expectations, even without receiving the influence from external environment and society rules. Therefore the gender control appeared to make sense, against that sort of self-fulfilling prophecy suggested by Carr and Steele; by the way, a certain degree of uncertainty keeps high in interpretating the results and the possible crossing of different effects and omitted variables. Tinkler et al. (2016) investigated venture capitalists' funding decisions in high-growth and high-tech entrepreneurship: women resulted to receive higher evaluation by VCs when the assessment moment happened with close contact. When in presence of technical background of both male and female entrepreneurs, the VC evaluation did not register variations among genders, but when technical background was absent and prior performance information ambiguous, the female entrepreneurs received lower evaluations than male non-technical entrepreneurs, sounding like women were supposed to be less competent and having less leadership ability when available information was insufficient. Such paper could let to intend that entrepreneurs' academic background moderated gender effect. Kluen et al. (2017) claimed that gender differences in anxiety management affect risky decision-making situations since acute anxiety escalates cortisol activity, which stresses

the risk attitude in men but not in women, thus driving to diverse behaviors under pressure; that is a strong evidence that gender differences in risky decision-making are explained as hormonal reaction too. Van den Bos (2012) underlined gender differences toward risk appetite, stating that women were more sensitive to occasional losses and, as consequence, needed more time before reaching the same level of performance if compared to men: so he justified women's minor Risk Appetite aptitude by using sensitivity to loss. Stanton et al. (2010) justifies gender differences in risk taking by invoking hormonal components, namely the endogenous level of testosterone: high testosterone levels seemed being correlated with greater risk-taking attitude, and this was true both in men and women individuals, so offering further hormonal explanation about Risk Appetite differences. Finally, Zhao and Zhang (2016) reported that people tend to trust strangers of opposite gender more than those of same gender, and females trust females much more than males trust males. So an emerged interesting point is that male teams (i.e., absolute absence of females mitigating contrasts) suffer more during coordination phase, and is perhaps more relevant into the scientific method, in which orchestrating feedback exchange activity is a core issue. In conclusion, the last and seventh research question aims to investigate whether gender* moderates PsyCap (focused on Risk Appetite), academic level and initial motivation effects on natural levels of scientificity and effectuation, while interacting with experience proxies (e.g. previous established ventures, experience in same sector), offering kind, startup industry, academic background. Please notice that the effectuative approach should be particularly interested as highlighted by the studies (Van den Bos, et al., 2012) on the sensitivity to occasional losses, since right such facet is a core component of the effectuative framework which also includes network, execution, flexibility and control abilities.

2. The research program and its scope

This thesis project draws on a RCT (Randomized & Controlled Trial) study realized at the turn of 2020 and 2021 in Italy and named InnoVentureLab (IVL), born thanks to the partnership between ICRIOS research centre of Bocconi University, Politecnico di Torino and Politecnico di Milano. As described in Bacco et al. (2020), the IVL program focuses on how entrepreneurs make decisions under conditions of high uncertainty. The purpose is to extend the prior few works which showed how entrepreneurs can improve ability to make key decisions for business development by adopting a set of practices labelled 'scientific approach'. As explained more times in other chapters, scientific approach is a set of rules based on strong emulation of what scientists do. When entrepreneurs use this approach, they accurately frame the problem they face, complying to the following steps:

*Blau_gender along with boolean categories such as female majority, female unanimity, at least one women

articulating theories, defining testable hypotheses, and conducting well setted tests while making thoughtful interpretations. A randomized controlled trial (RCT) was conducted to obtain robust evidence and test the impact of scientific approach vis-a-vis another popular approach to decision-making process, the so-called effectuation. When using such so different mindset, entrepreneurs are expected to exploit a non-predictive approach aimed to define the needed steps by gauging what resources they have. Building on other two pilot RCT studies realized in Italy (and counting 116 and 250 startuppers), IVL has the objective to extend the results over as many as 500 entrepreneurs of new startups, measuring the diverse effects generated by both effectuation and scientific approaches to decision-making, while deeply investigating if they differently act by modifying the boundary conditions.

The program got started on 1st May 2020 and scheduled to end on 28th February 2022: it provides entrepreneurs with eight different sessions of training that, seen the pandemic situation, have been supplied with mandatory online mode. Each session is composed of interactive lectures, along with coaching lesson by qualified mentors and instructors, everyone working with a sub-group of the entire sample. Both treated and control startups received the identical number of lessons about entrepreneurship, where the primary topics are:

- BMC (Business Model Canvas), useful and widespread tool introduced by Osterwalder and Pigneur (2005), it is used to efficiently frame the various components of an entrepreneurial idea and its business model;

- effective ways to do polls, interviews and surveys, other than the respective best practices, with the objective of making data collection without personal, socio-economic and psychological biases, while choosing the right pool of respondents (i.e., absence of selection and auto-selection biases) and finally analysing results by considering the most appropriate criteria;

- Minimum Viable Product (MVP), essential means useful for pursuing only the worthy ideas since it allows to conduct tests and minimize resource investment while making easier the information exchange between startup team and its own environment;

- concierge/prototype (respectively referred to service/product) conception, both aimed to facing the real market needs by creating a pilot version following right procedures, timing and requirement-feature balance.

Given the alike contents proposed in both treatment and control group, the difference took place in the scientific routines applied to entrepreneurial decision-making framework taught only in the first treatment class, meanwhile a specific teaching has been done on the other treated group, by using the flexibility provisions suggested by

effectuative method. The control group could have the possibility to receive learning insights neither about scientific nor about effectuation approaches. A final sub-group of entrepreneurs did not receive any training. All the groups received exactly the same number of hours in training, in order to ensure comparability in terms of pathways and therefore of results. On American Economic Association registry website - *socialscienceregistry.org* - it is also possible to consult official details and future developments about the InnoVentureLab program. There, the major outcomes and research questions (final purpose of the whole research study) are specified:

i) income flows - represent the main dependent variable and are measured as € (euros);

ii) dropout – binary variable, assuming value 0 until the firm abandons the learning program and entrepreneur ceases the startup activities (severe controls have to be made in order to ensure the actual venture ending), while assuming value 1 right when the startup concretely drops out;

iii) pivot – meant as cumulative amount of times in which an entrepreneur makes relevant changes to business model, where "relevance" arises every time he moved from original to another business idea by modifying the core value proposition.

The whole research examines other potential dynamics too: e.g., gathering values on variables strictly related to timing and means utilized in entrepreneurial decision-making process. In particular, the precision in predictions and esteems results as a key aspect, so that it is observed in the starting instant of time and even throughout the course development, since the expected and desirable effect is its pronounced improvement due to scientific treatment. Furthermore, other co-variables have been gathered about several features, useful to be employed in role of covariates interacting with treatments: gender, psychological traits, perceived competitiveness, information sharing, management practices, wellbeing, insight accumulated and developed, passion and communication, as well as common knowledge within the team, mentors' influence, prior experience and work/academic background.

2.1 Sampling and design experiment

The RCT study in progress at the turn of 2020 and 2021 considers uniquely the nascent entrepreneurs, meant as those starting a new business at the moment, while there are no restrictions about the industry belonging. IVL was promoted on numerous digital channels, in terms of a general course able to provide participants with useful insights on creation of new innovative enterprises. In addition, both sign up and participation are completely

free of charge, having the purpose of catching entrepreneurs with limited economic resources. Multiple instructors received specific training before the program delivery since the teaching materials they used were accurately designed for that precise objective. Each instructor teaches three classes (i.e. scientific treatment, effectuation treatment, control sub-set). Meanwhile the research team - of which I took part in role of research assistant (RA) - has been in charge of designing the time evolution of the activities, while coordinating and overseeing them, so as to ensure the correct progress of taught modules and coaching sessions, avoiding technical and management issues whereas instructors carry out their lessons. The sample composition was made recurring to pure parallel randomization model, supported by STATA statistical software. The definitive resulting sets are four: scientific treatment, effectuation treatment, control (i.e. neutral training) and pure control (i.e. no training). After startups being randomly assigned into one of the four groups, multiple sub-groups of 35 startups were randomly matched with the coaches, so that each coach got three sub-sets of startups. The reference unit during the randomization process was the solo startup, while randomization discriminants were comparison among mean values and t-test across groups; minimum detectable effect size was observed for the main outcomes. The overall sample extent counts 500 startups, homogeneously divided into the following groups: 125 in the scientific group, 125 in the effectuative group, 125 startups in the control group (neutral training) and the last 125 in the pure control one (absence of training).

2.2 Why RCT design

As underlined into the prior paragraphs, the whole IVL program experiment bases on a randomized and controlled design, because of the particular purpose: the observations have to be accurate and able to discern between the different effects, so that a rigorous setting is needed to provide robust results not affected by distortions and disturbing influences. Indeed, the dataset naturally exists as not-experimental data (i.e. not ideal shape), since the most frequents working conditions are under observational setting: the analyses come from real behavior observation, so an empirical study leading to a number of risks, namely omitted variables, simultaneous causality (ambiguous verse in cause-effect relation) and presence of correlations not necessarily implying causality.

Such complications call for precise procedures to follow (Stock & Watson, 2012), first of all at experiment level. A causal (and not a casual) effect can be effectively well measured only in restricted situations, such as the following features:

- experimental design - the participants have not the possibility to choose the treated individuals, ignoring the existence of different groups under different conditions;

- controlled – the research team, including RAs, is in charge of assigning the treatments while selecting the control and pure control sets, aiming to gauge differential effect between treatment and absence of treatment;

- randomized, even named casualized – to be meant not as literally casual, that is a common misinterpretation, but in terms of equiprobability, thus the treatment received assignment by respecting random criterion in order to avoid systematic correlation between characteristics which are external to the observation, often linked to environment and specific belonging to group (e.g. such barrier provokes that, in case the research team could not choose the distribution of startups among sub-groups, it would have been impossible to compute the pulled standard deviation of the reference population, given the potential belonging of startups to diverse populations);

- pseudo ideal – meaning everyone follows the program protocol, by entirely complying to the imposed rules, delivering correct reports, following the scheduled timing and so on.

Such care is due to necessity of being sure to measure the effect generated by real the regressors, that is, with no external influences which may interfere into the relationships of interest: these are undesired components affecting the experiment, and may derive from other features other than the observed ones, like dynamics tied to belonging to a group rather than another, and any other environmental factor. An explicative instance is offered, again, by Stock and Watson (2012): they proposed the situation in which the experiment consists of observation on several cultivated fields, where the treatment is about the fertilizing power; therefore, the farmer, in role of research team, does selection with the purpose of deciding whether a certain field will be treated with fertilizer or not. Thus, the issue arises in the moment when some lands, while others not, are strongly hit by sunlight during the morning time: this is a classic example of variable due to group belonging, having the power to affect final outcomes, given that improvement in field productivity and other outcomes keep relevant ambiguousness about which is the real reason provoking the differences in the used metrics, making more difficult to infer in robust statistical terms.

An effective answer to the presented problems suggested for precise procedures to follow during an econometric experiment: the scholar, first of all, must chose the hypotheses to verify, that is construction of economic theory even drawing on prior evidences emerging from scientific literature; here, the independent variables are selected along with their internal relations. So, it comes to specification of econometric model, consisting of assumptions on regressors' nature and their bond to residual error, leading to functional form generation too, and conjectures about nature and probability distribution of the residual errors. Indeed, it is useful to remind that the residual component is an aleatory variable, needing of be defined by expected value and statistical distribution, while considering it could include omitted factors affecting the dependent variable,

other than errors born in measuring the values of dependent variable.

Yet, the next step is data collection, with the aim of calculating unknown population parameters by exploiting observations on sample and discerning between the different types of dataset (i.e. cross-sectional, panel and time series); then, the scholar proceeds to the quantitative esteems of econometric model by utilizing the available means, such as the Ordinary Least Squares method (OLS), in order to obtain the estimators' values while assuming simple casual sampling. Finally, it comes to firstly specification assessment, controlling for consistence among assumptions and economic data, namely verifying that no relevant regressors have been excluded, whereas controlling ex-post for the nature of functional form, residual error's nature and regressors' meaning. Secondly, the last control is done on the correlation verse, being consistent with economic theory, and in conclusion the econometric model is ready to test the desired hypotheses, as well as make predictions and simulate alternative scenarios.

2.3 Gauss-Markov Theorem: the OLS efficiency

An Ordinary Least Squares model (OLS) is adopted into the linear regressions reported in this thesis project since - other than being the most popular and widespread means used in econometric field - it appears to be the best in such experiment design. The OLS estimator is obtained by minimizing the sum of the squared errors, where error stands for difference between actual value (observed thanks to empirical experience) and predicted value, inferred by the regression model. OLS is not distorted and consistent. To have correct OLS estimators, the necessary and sufficient condition imposes truthless about the so-called *least squares' assumptions*. Firstly, the residual error's probability distribution conditioned to the independent variable must have null mean value, namely the estimator is not statistically distorted, that is always true in an ideal randomized controlled experiment (e.g. the research team decides which participants belong to which groups); in other words, the residual errors are independent respect to regressors, given that they are definitely random and then get minimal extent, so null average value.

Secondly, regressor and dependent variable for each observation are identically (units selected from the same population) ed independently (units casually selected so that regressor and dependent variable of different units do not get mutual influence) distributed - and this is surely true when using simple random sampling. Such assumptions can be never verified if the experiment registers variations of the same unit through the time, in presence of time-invariant factors. Finally, the outliers both in regressor and dependent variable must be rare, that is in technical terms having finite fourth moments: if not verified, the estimator of the population parameter is inconsistent, so becomes important to carefully understand whether the distortion is due to wrong measures, data not belonging to the right dataset,

codification error, and so on. In addition, two further assumptions usually add to the basic set, though they represent unlikely cases observable into the real world: homoscedastic residual error (Frisch, 1926) and residual following Gaussian probability distribution, characterized with parameter σ^2 as variance and null in average.

Thus the Gauss-Markov theorem asserts that - if the first four assumptions are considered true within the design experiment - then the OLS estimator becomes the most efficient one among all the linear estimators, where efficiency gets the meaning of minimum variance, and linear estimator stands for linear function of dependent variables for each observation. Instead, if the totality of five assumptions is true, then OLS obtains the lowest variance among all the consistent statistical estimators (even if not linear), if the sample counts infinitely great numerosity. Anyway, the OLS model would be highly sensitive to outliers, if compared with other estimators, where sensitivity stands for major variance; so that, in presence of numerous outliers it is advisable recurring to alternative position indicator (such as median value) in order to significantly observe less variance, reminding that the more average and median are near, the more unlikely are the outliers.

2.4 Marketing and sponsorship

The InnoVentureLab program has been conducted thanks to the coordination and support of a number of people, including RAs as well as PhD students, university teachers, instructors, academic researchers and others. The involvement of a such great amount of individuals called for high structured activities, along with well-defined procedures and use of dedicated tools. Additionally, the whole program unified the efforts of three prestigious universities: Bocconi University, Politecnico di Torino and Politecnico di Milano, all avantgarde centres in several fields of knowledge, from economics passing by technological subjects such as engineering and architecture. As in any large organization, the coordination is a core point needed to the effectiveness of the overall work. The program has been carried out in different cities and countries throughout the time, lately in Italy and UK (London), whereas this year two parallel flows are conducted at the turn of 2020 and 2021: one in Italy and another simultaneously in India. One of the first activities requiring a well-orchestrated coordination was the marketing journey, thought for the IVL program on different digital channels; obviously, the vis-à-vis advertising in other athenaeums, or in high school environments and professional clusters, was forbidden given the challenging situation of global pandemic.

So each kind of promotion activity was conducted online, avoiding direct contact during the initial phase as successively during data collection: all the people involved have been divided into sub-groups, with the aim of using different social networks and online channels to push the program toward the future entrepreneurs, and the utilized means have showed effectiveness seen that the amount of entrepreneurs participating to IVL resulted sizable. The program

gathered a large pool of participants since it was free of charge, hosted ventures belonging to any industry and called for entrepreneurs coming from south, centre and north of Italy (even if only early-stage startups), a condition made possible by the pandemic situation, which allowed to overtake the barriers once represented by physical presence and travel time. High sampling numerosity and heterogenous composition are both a key factor for the effectiveness of a RCT experiment, remembering that the main objective is to indagate correlation between internal-to-team features and scientific decision-making as well as effectuative decision-making, and their influence on final outcomes in performance, while controlling for potential differences by varying boundary conditions. The marketing campaign got started in the summer of 2020, seen that the program begin was scheduled in October 2020. The marketing activities were first of all divided taking into consideration the RAs' belonging to one of the three involved universities, as the coordination would have been easier. Some cloud platforms and project management apps were needed during the campaign: Google Drive and Dropbox for file sharing, whereas Doodle, Slack and Trello were used as calendars and effective scheduling, other than task checking and assigning. Yet, given the pandemic, some online platforms have been fundamental for the program success, such as Skype, Zoom, Google Meet and Microsoft Teams, useful to organize lessons as well as conference and meeting. The summery marketing campaign purpose was achievement and activation of an enough more widespread target, compared to that obtained in the prior years: it focused on a particular segment (early-stage startup), through online platforms as Facebook, Instagram, LinkedIn, specialized websites, direct contacts, incubators, accelerators and co-working centres established all along the Italian territory. Particularly, the reference social channels have been chosen according to carefully assessment, based on social network's nature and kind of enrolees.

LinkedIn was strongly considered because of its working nature and, above all, because its enrolees usually use it mainly for professional objective, so that, the contacts kept on such platforms and type of shared contents are in line with the scope of IVL program and marketing campaign. LinkedIn was exactly born with the objective of making network development, able to tie entrepreneurs deriving from any background with workers, professionals, employees, accomplished firms and institutions. Furthermore, Instagram was selected given the great popularity and massive presence of young people, including students and new ventures founders, which could be reached by our advertising in an effective way through the wide range of social tools provided by the platform, such as promoted posts, Ig stories and targeted advertising campaigns. Finally, Facebook was the main channel to promote the activities, since it gave the possibility of diffusing highly segmented contents on various dedicated groups, if accurately located in the search bar. Indeed, the great amount of effort employed in such activity lead to find a lot of groups about topics of interest, such as entrepreneurship, technology, innovation, but also early-stage startups, incubator environment, innovative accelerators,

ideas' exchange, network research and, more in general, attempts to connect different points of view and human backgrounds aimed to create new and disruptive power.

The social network campaign was carried out by publicizing a series of dedicated contents on each platform, following a pre-setted scheduling; the used means were a set of social pages, named InnoVentureLab, expressly created in order to promote the event and make the name ascribable to something new: an innovative program offering innovative type of contents organized in innovative way. The social pages were coordinated and in line with a common design (e.g., same use of house colour), because of the necessity of making immediately recognizable the utilized template and brand.

The first step of internal organization was referred to create a certain number of task-force teams, in order to foster an easier coordination in smaller sub-groups divided according to university belonging: in each team, the individuals accounted for a specific segment on a specific channel, so that avoiding overlapping and duplicated activities, which could be perceived as undesired spamming, that is an effect to absolutely prevent. Among research subgroup members, the social network campaign was divided. The great amount of contents shared via digital marketing allowed to reach great players belonging to entrepreneurship: for instance, Plug&Play enterprise was named as official partner of IVL program, because of its fundamental commitment at international level in encouraging technology development by following the most favourable trends, working as trait d'union platform between big companies and the best highly technological startups. Startup Grind is a further protagonist in the partnership network created by IVL: it resulted helpful given that represents one of the widest communities grouping students, investors and entrepreneurs. A large pool of different types of collaborations also includes Start Up Legal, which is involved in legal and financial support addressing startup and young ventures, with assistance throughout the entire enterprise lifespan, from born to funders entry. Yet, VGen was selected as further partner since it is employed in open innovation environment, while connecting great companies and young students through an innovative and continuously diffusing tool nowadays, that is the virtual internship. In addition, the IVL marketing campaign was boosted also thanks to the contribution offered by large online authors and forums (i.e. 100.000+ followers on social pages), so that the right amount of visibility could be guaranteed through digital channels during the reduced time horizon needed to gather the necessary subscriptions.

2.5 The data collection

The first step was referred to the measure of the startup natural orientation towards scientificity and effectuation in decision-making process, other than potential variations due to the effect produced by boundary conditions. Then, the research assistants proceeded to the collection of a number of different types of data, referring both to team composition and leader's features, psychological and orientation traits. Yet, were tracked some

qualitative characteristics of venture and leader's perception - such as proposed offering, reference industry, working and academic previous experience, academic background, potential prior direct collaborations among team members - as well as quantitative ones - as team numerosity, hours invested on startup, perceived weight of each business aspect on the entrepreneurial success. Additionally, all the demographic features were detected, in order gender, average team age, detailed geographical provenance. Every variable previously explicited has been captured throughout all the program, that is, in several successive instants of time in order to track development. The used tools were mainly survey, telephone interview and Qualtrics platform, all items generated thanks to the contribute of research team, and pursued by the whole pool of research assistants. The first data gathering started at the end of summer 2020 counting on survey and telephone one-to-one interviews. The first tranche of information was got during the finalisation of the registration step, using online questionnaires and resume templates. Then, after the selection phase, the RAs contacted all the team leaders by phone in order to gather information about orientation towards scientificity and effectuation in decision-making registered at time zero, with the purpose of understand and analyse the natural aptitudes before of treatment, while filling up the vacations left into the online questionnaires.

As it is possible to view in Figure 1 in order (from left to right, from top to bottom), the first Pre-Survey proposed as many as 121 questions aimed to intercept a lot of different information about the respondents: they range from demographical and registry items to questions focused on prior experiences, from academic background to the dedicated effort on entrepreneurial tasks, from the offering kind to the other activities in which the team members are involved, from previous collaborations among co-founders up to the key features in which the team is expected to distinguish if compared to competitors. Instead, the final long displayed list was created with the objective of capturing psychological and aptitudinal orientations of team leaders as well as startups at overall level, by asking indirect and non-tendentious queries about their behaviors during the real-life situations of a typical entrepreneur. The variables reported in Figure 1 provided personal insights on participants, in order to make possible a successive analysis about internal differences among the demographical aspects, other than using them as controlling variables for secondary effects in case the environmental influences arise.

The team numerosity was detected to be used as verification of composition and as index about the components of heterogeneity indicators, other than in gauging the total commitment of hours assigned to the entrepenurial occupation. After, each entrepreneur should talk about the kind of offering treated in his own business, by choosing from a range including product, service and Other (in this case, it was requested for further specification into the following question) options. Radio button answer mode was often used to try of better categorizing the gathered answers, namely create highly structured template for the experiment design. Yet, the entrepreneurs had to

provide the average amount of weekly hours invested by each team member on startup work, so data are simple numbers; moreover, the respondent gave information about potential other commitments added to the business idea treated in IVL, with the aim of exploiting such insight to measure the extent of commitment employed on entrepreneurial activities. Then, a series of background parameters are asked:

- current studies – to be chosen between bachelor degree, master degree, master in business and administration, doctorate and other specializing courses post-lauream;

- main subject of the studies – to be chosen between architecture & design, physics and maths, economics & management, ICT, engineering, law, medicine and biology, political and social sciences, historical and philosophical sciences, and Others (in this case, successive specification was mandatory);

- Bachelor of Science – boolean and, if Yes was the answer, it was asked about specific subject between the classes previously categorized;

- Master of Science – boolean and, if Yes was the answer, it was asked about specific subject between the classes previously categorized;

- MBA & similar - boolean and, if Yes was the answer, it was asked about specific subject between the classes previously categorized;

- Doctorate - boolean and, if Yes was the answer, it was asked about specific subject between the classes previously categorized.

Thus, it was asked to specify whether other occupations were present for each respondent (selecting between full-time and part-time too); so, further information about kind of work was requested to insert. Additionally, a number of questions focused on prior work experiences and their industry belonging, along with those on prior roles of executives, previous established firms and relative business planning activities. Yet, some points involved possible economics, management and/or entrepreneurship education courses already attended, while controlling for the horizontal (or vertical) nature of academic studies. Six questions were about previous direct collaborations among team members, both at university and work levels, before of asking about the key competitive and differentiating factors perceived by business owners. In conclusion, the last 48 queries tried to intercept some psychological and personal traits of the team decision-makers, each one underlying to specific more abstract factors to be analysed in view of scientific/effectuative orientations. Such last questions are all expressed on 7-points Likert's scale, as suggested in the approved and largely diffused Likert and Murphy (1932) essay, where zero value stands for complete disagree while the seven score stands for complete agreement.

In Figure 2, instead, the outcomes deriving from on-phone interviews made by RAs are reported: the variables are expressed on 5-points Likert's scale, where value 1 stands for minimum level in the considered characteristic, while 5 represents the maximum degree for the respective characteristic, and value zero is chosen when the feature does not exhibit. As explained throughout the prior paragraphs, the scientific approach consists of four primary phases (highlighted with light green colour), being theory formulation, hypotheses statement, test conduction and validation, along with a precise and consistent quantitative threshold useful at the crucial moment of choosing between pursuing the entrepreneurial idea, pivoting and abandoning it. These are all steps to strictly follow, by using well-structured paths and rigorous tools, right like a scholar or scientific researcher. For each of the 5 illustrated macro categories, the simple arithmetic mean has been computed and, at overall level, the average of the averages is calculated in order to resume the totality of information on scientific inclination into a single indicator, to be compared with the other variables of interest subject of study in the experiment.

Meanwhile, also the variables underlying for effectuation approach to decision-making process are displayed (showed with red colour). Again, they are expressed on 5-points Likert's scale, where value 1 stands for minimum level in the considered characteristic, while 5 represents the maximum degree and value zero is chosen when the feature does not exhibit. The variables range from bird in hand attitude (i.e., exploiting the owned personal resources such as network, abilities, passion and background) until pilot plane capability (controlling and executing instead of waiting for predicted events), passing through affordable loss (focus on the maximum available), crazy quilt (proactivity in keeping contacts with customers, suppliers, competitors) and lemonade (exploiting unexpected situations counting on flexibility and preexisting resources) aptitudes. Still, for each of the 5 discussed macro categories, the simple arithmetic mean has been computed and the overall average of the averages is calculated, with the objective of summarizing the whole information about effectuative propensity into just one quantitative indicator.

startup name	PhD	relevance in your business-offering usability	I will found a firm in order to become rich
name	PhD subject	relevance in your business-offering design	I will found a firm in order to move up into the business world
surname	PhD subject-specify	relevance in your business-offering other features	I will found a firm in order to solve a specific problem faced by people with which I strongly identify
CF	currently you are:	relevance in your business-offering other features (specify and give mark)	I will found a firm in order to have a proactive role in shaping the activities of people with which I strongly identify
gender	work kind	I can predict my corporate's market demand	I will found a firm in order to solve a social problem which private firms are not usually able to face
birth year	work kind-specify	I can carefully predict when bigger competitors will enter my market	I will found a firm in order to have a proactive role in changing the way by which the world acts
birth country	working experience years	I can make my corporate successful even if others could fail	In role of founder, it will be very important for me to manage my firm basing on robust management practices
domicile country	working experience years - startup industry	I like to experience bold actions dealing with unknown	In role of founder, it will be very important for me to deeply analyse financial predictions of my business
domicile region	working experience industry	I would invest time and/or money on initiatives with potential high yield	In role of founder, it will be very important for me to supply offering useful to people with which I strongly identify
domicile province	working experience industry - specify	I tend to act with bravery in high risk situations	In role of founder, it will be very important for me to show my customers that I agree with their opinions, interests and values
domicile city	working experience years as executive	I like to experience new activities but not necessarily risky	In role of founder, it will be very important for me to be highly conscientious world citizen
REP boolean	already established other companies before entering in such startup	When involved in projects I prefer testing unique approaches rather than reconsider the already used ones	In role of founder, it will be very important for me to make the world a better place
REP name	#companies established before entering in such startup	In order to learn I prefer testing personal ways rather than those used by the others	When I will handle my corporate, it will be very important to focus on what my firm can obtain if compared with competitors
REP phone	experience in Business Plan writing	I prefer a new problem-solving approach rather than approaches already used by myself or others	When I will handle my corporate, it will be very important to establish a strong competitive advantage on competitors
startup #members	attended academic courses about economics/management	I usually act in order to avoid future issues, needs or changes	When I will handle my corporate, it will be very important to focus on people with which I strongly identify
offering	attended academic courses about entrepreneurship	I tend to plan my projects in advance	When I will handle my corporate, it will be very important to support people with which I strongly identify
offering-specify	my academic competences are highly specialized in a certain field	I prefer to personally carry out the projects in which involved rather than waiting for someone else doing it	When I will handle my corporate, it will be very important to focus on what my firm can do for social welfare
weekly hours on startup	during my academic path I developed equal competences in a number of fields	I tend to face with challenging working tasks which can teach me a lot	When I will handle my corporate, it will be very important to persuade others that private firms are able to face social problems like those challenged by my firm
current other commitment	thanks to my academic studies I am able to complete few tasks but with great mastery	I continuously search for opportunities useful to develop new capabilities and knowledge	Please indicate how much effort you employed in understanding decision processes of the other team members
studying	thanks to my academic studies I am able to complete many different tasks	I like difficult work tasks by which I can develop new capabilities	Please indicate how much effort you employed in using devices appropriate to remotely work together on the business idea
subject	did you attend, even if in different periods, the same university of at least one of the other team members?	For me, the possibility to develop work abilities is so important to take a risk	Please indicate how much effort you employed in work together in presence on the business idea
subject-specify	who?	I prefer to work in situations calling for high capability and talent	Please indicate how much effort you employed in generating a common dictionary with the other team members
B.Sc.	did you work, even if in different periods, in the same corporate where at least one of the other team members worked?	I deeply care about to demonstrate that I can achieve better outcomes if compared with colleagues	do you know other entrepreneurs candidates to InnoVentureLab?
B.Sc. subject	who?	I try to understand what is needed to demonstrate my capabilities when I work	who?
B.Sc. subject-specify	before working on this business idea, did you have work or study collaborations with another team member?	I like when the other colleagues are aware of my well working	Did a participant of TheStartupTraining or TheStartupLab suggest our program to you?
M.Sc.	who?	I prefer to be involved in projects where I can demonstrate my capabilities to others	who?
M.Sc. Subject	dimensions in which your business idea distinguishes if compared with similar	I prefer to avoid new tasks if I could appear incompetent if compared to the others	Do you remember 3 books (about business and/or startups) which particularly influenced you?
M.Sc. subject-specify	Other features of the offering - specify	For me, it is more important to avoid showing low ability than learning something new	If yes, please indicate the top 3 list - number 1
Master	relevance in your business-price/cost of the offering	I worry about starting a new working activity if my outcomes could demonstrate I have low competences	If yes, please indicate the top 3 list - number 2
Master subject	relevance in your business-offering quality	I prefer to avoid work situations in which I could get bad results	If yes, please indicate the top 3 list - number 3
Master subject-specify			

Figure 1: first pre survey - script

VARIABLE	DESCRIPTION	CODIFICATION
Data intervista	Data della chiamate	date
Intervistatore	Nome e Cognome della persona che fa la chiamata	string
Startup	Nome startup	string
Referente	Nome referente (persona intervistata)	string
Numero di ore lavorative	Numero di ore medie che ciascun membro del team dedica alla startup settimanalmente	number
Clear_definition_roles	Hanno una chiara divisione dei ruoli?	1-5
Definition of milestones	Hanno obiettivi chiari secondo cui organizzano il lavoro?	1-5
Decision_maker	Chi è il principale decision-maker (ruolo, nome)	string
Gerarchia (SI/NO)	Prendono le decisioni seguendo una gerarchia?	boolean
Unanimità (SI/NO)	Prendono le decisioni insieme e solo se tutti d'accordo?	boolean
Maggioranza (SI/NO)	Prendono le decisioni in base a quello che pensa la maggioranza?	boolean
Fase_startup	In che fase si trova la startup (vedi lista nello script)	1-5
FEEDBACK	Se hanno ricevuto feedback da esperti, mentori, altri imprenditori, amici, familiari, ecc. oppure no	boolean
Feedback_expert	Feedback_expert 1 - hanno ricevuto feedback da esperti (ad es. Mentore, imprenditore esperto, altro esperto nel loro campo, ecc.), altrimenti 0	1-0
Feedback_negative	Feedback_negative 1 - hanno ricevuto un feedback negativo, 0 altrimenti	1-0
Feedback_change	Feedback_change 1 – se cambiano qualcosa sulla base del feedback riportare 1, 0 altrimenti	1-0
Competitor_close	riportare numero, se imprenditore è incerto chiedere se più o meno di 10 o stima approssimativa	number
Competitor_broad	riportare numero, se imprenditore è incerto chiedere se più o meno di 10 o stima approssimativa	number
Teoria_chiara	La teoria è comprensibile (falsificabilità)	0-5
Teoria_elaborata	La teoria va nel dettaglio (falsificabilità)	0-5
Teoria_alternative	La teoria considera aspetti alternativi (generalizzabilità)	0-5
Teoria_evidenza	La teoria ha dei dati a supporto	0-5
Teoria_modulare	La teoria scompone il problema in sotto-problemi da risolvere	0-5
Teoria_gerarchia	La teoria aiuta a prioritizzare i problemi da risolvere	0-5
Ipo_esplicite	Elenca le ipotesi che intende testare in modo esplicito	0-5
Ipo_coerenti	Le ipotesi sono derivate dalla teoria	0-5
Ipo_precise	Le ipotesi sono formulate in modo da testare una cosa alla volta	0-5
Ipo_falsificabili	Sono in grado di stabilire una condizione (soglia) in base alla quale le ipotesi possono essere considerate supportate o meno	0-5
Ipo_testabili	Le ipotesi sono formulate in modo che le variabili da testare possano essere operazionalizzate (=trasformate in misure) correttamente	0-5
Ipo_alternativa	Le ipotesi erano mirate a falsificare una cosa e a supportarne un'altra come conseguenza diretta (alternativa)	0-5
Test_coerenti	Il test è coerente con le ipotesi (permette di testare le ipotesi)	0-5
Test_validi	Specificità: il test è fatto nel vero contesto in cui opera la startup Validità: Il utilizza metriche coerenti con il costrutto teorico Affidabilità: il test utilizza misure ripetibili con un basso errore di misurazione	0-5
Test_rappresentativi	Il test coinvolge un campione con le caratteristiche del reale target della startup	0-5
Test_rigorosi	Usano il test giusto e con le procedure giuste (es. domande aperte nelle interviste; o hanno una baseline di confronto o un contraffattuale nel test)	0-5
Test_causalità	Il test misura un nesso di causalità tra le 2 variabili testate (se Variabile1 allora effetto su Variabile2)	0-5
Test_bias	Il test è realizzato su un campione con bias ridotti di selezione e autoselezione	0-5
Val_dati	I dati raccolti non si basano su esperienze individuali o sensazioni	0-5
Val_misure	I dati raccolti misurano quello che teoricamente l'imprenditore vuole misurare e sono dati affidabili	0-5
Val_sistematic	c'è un modello di metriche, uno schema, qualcosa che categorizzi la raccolta dati	0-5
Val_esplicativi	riesce a connettere i vari risultati e a rielaborare la propria teoria conseguentemente	0-5
Val_stima	Se gli imprenditori hanno una misura di performance in base alla quale stimano il valore dell'idea al fine di prendere la decisione finale (Continua/Pivot/Exit)	0-5
Val_componente	Evidenze dei test (relativi a specifiche ipotesi) sono tradotte in una stima del valore della componente del modello di business testata	0-5
Val_alternativa	I dati raccolti aiutano a stimare il valore della componente alternativa a quella testata	0-5
Val_negativa	I risultati negativi dei test permettono di capire nuove possibilità di esplorazione	0-5
Decisione_soglia	Se la decisione di 1. continuare o abbandonare il progetto è stata presa confrontando la stima del valore dell'idea con una soglia minima 2. modificare il progetto è stata presa confrontando la stima del valore dell'idea con una soglia minima	0-5
Decisione_soglia_calibrata	La soglia tiene conto della qualità dei test e del tipo di dato raccolto	0-5
Bird_in_hand_whoare	Misura in cui sviluppano l'idea partendo da chi sono, ossia dalle proprie abilità e capacità	0-5
Bird_in_hand_whoknow	Misura in cui sviluppano l'idea partendo da chi conoscono, ossia dalla propria famiglia, amici, network lavorativo	0-5
Bird_in_hand_whatknow	Misura in cui sviluppano l'idea partendo da cosa conoscono, ossia dal proprio background e esperienza	0-5
Affordable_loss_max	L'imprenditore ha usato il massimo delle risorse che può permettersi di perdere	0-5
Affordable_loss_risk	L'imprenditore non ha aggiunto risorse (anche soldi) a quelle disposte inizialmente	0-5
Affordable_loss_focus	L'imprenditore ha focalizzato la sua attenzione a non perdere più di quanto può permettersi invece di focalizzarsi sul valore atteso	0-5
Crazy_quilt_competitor	Se l'imprenditore ha stretto partnerships o alleanze con possibili competitor	0-5
Crazy_quilt_supply	Se l'imprenditore ha ridotto l'incertezza stringendo accordi con fornitori che hanno mostrato interesse prima della commercializzazione	0-5
Crazy_quilt_client	Se l'imprenditore ha ridotto l'incertezza stringendo accordi con clienti che hanno mostrato interesse prima della commercializzazione	0-5
Lemonade_surprise	Misura in cui hanno cercato di sfruttare eventi inattesi (nuove informazioni, nuovi incontri, sorprese)	0-5
Lemonade_adapt	Misura in cui adattano le loro scelte alle risorse a disposizione e non viceversa	0-5
Lemonade_opportunity	Misura in cui hanno approfittato di nuove opportunità che sono emerse	0-5
Lemonade_flexibility	Misura in cui considerano la flessibilità come un valore da preservare	0-5
Pilot_plane_control	Il focus è su quelle attività che l'imprenditore conosce bene e può controllare, invece di affidarsi a previsioni	0-5
Pilot_plane_exec	Il focus è sull'execution invece che aspettare di vedere cosa succede	0-5
Contingency_plan	Quanto è dettagliato il loro pensiero su cosa fare in questo caso (se una grande azienda dovesse entrare nel loro mercato)	0-10

Figure 2: first datapoint by telephone contact - script

3. Sample analysis and preliminary observations

This thesis work is based on data gathered at the initial step of the program, so that the reference sample includes 542 records: it grouped the team leaders of each startup, as well as all the other team members who accepted to answer interviews and surveys. Then, first the following analysis will include the descriptive statistics according to what emerged from such pool of respondents.

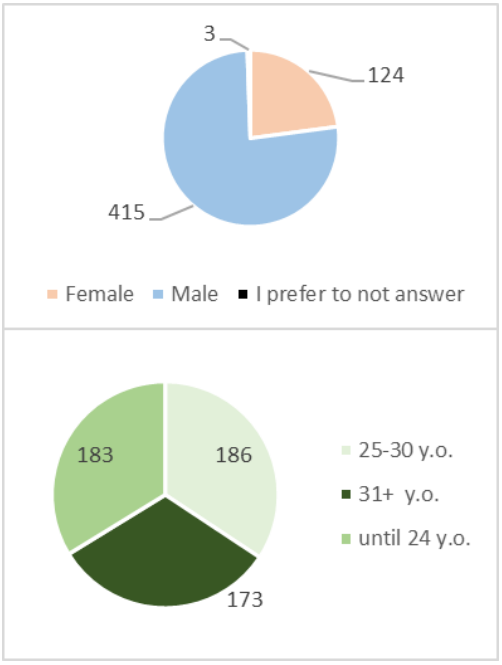


Figure 3: gender and age distribution

In Figure 3 it is possible to note that there is heterogeneous distribution of the gender, seen that male individuals are almost four times greater than females. Instead, looking at the age declared by every entrepreneur, is has been necessary to proceed with clustering by age range, with the purpose of generating three different but homogeneous groups in terms of numerousness, as they may be comparable this way. Obviously, due to the IVL nature and scope of the project (i.e., young enterprises as well as highly innovative backgrounds and ideas), the average seniority measured in the sample was minimum, so that the three clusters used relatively low thresholds: 24 years old separates the first set, while 30 years old is the higher threshold. The most of participants are very young, declaring to be 24 or less; the set of the oldest ones (i.e. starting from 31 years) counts 173 individuals, so becoming the less populous of the three. Again, if considered the demographical features, it is important to analyze the participants' origin. As observable in Figure 4, the experiment design and pandemic scope allowed to attract entrepreneurs from all the national territory, registering the majority of subscriptions within the regions of in order Lombardia and Piemonte. Anyway, there is strong presence of regions belonging to south and centre of Italy: 90 of 542 individuals have domicile in the south of Italy, against 96 from the centre and 306 from the north (50 are blank values, namely who did not declare his own domicile address).

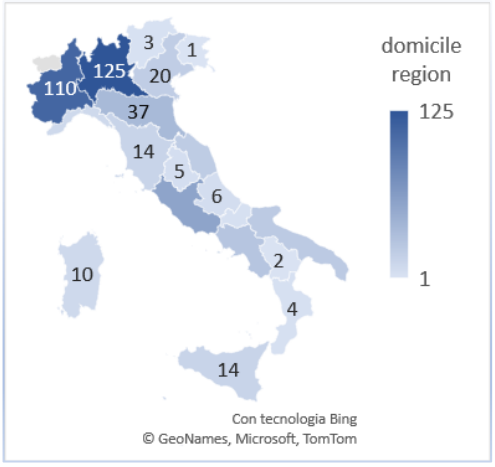


Figure 4: geographical distribution

The clustering process executed on the age was needed since defined as preparatory to the successive computation of diversity indicators (e.g. Blau's index). Indeed, the heterogeneity measure calls for division in categorical sub-groups, being carefully selected according to keep internal homogeneity within the group in order to better detect external heterogeneities. However, a more precise overview on the age distribution is guaranteed by the probability distribution (expressed in terms of relative frequency) in Figure 5, where the ratio of each seniority level is computed as well as displayed in percentual terms, referred to the totality of 542 participants. It appears evident how the modal value corresponds to the 24 years old level, that is the reason why it had been chosen as first threshold of the three different ranges. The right tail is longer and confirms presence of a reduced pool of older entrepreneurs, a natural phenomenon given the nature and the marketing channels of InnoVentureLab. Almost the total amount of individuals is grouped between 19 and 35 years, while the second and third more frequent values recorded into this sample are respectively 27 (41 times out of 542) and 28 (37 times out of 542). A strong polarization around the twenty-four value can be due to the fact that it represents the average age at which students usually achieve an academic title equivalent to master degree or, more in general, at which the university students conclude their own academic path. The criterion adopted to choose the second threshold is that such limit (thirty years old) exactly located on the 68th percentile, that sounds like something similar to the established partition utilized when a density distribution is decomposed in three parts, according to three-sigma criterion applied on percentile figures - which usually cuts the probability area subtended under the curve, in order to put the limits in correspondence of precise values which can differ according to the standard deviation and to the adopted convention.

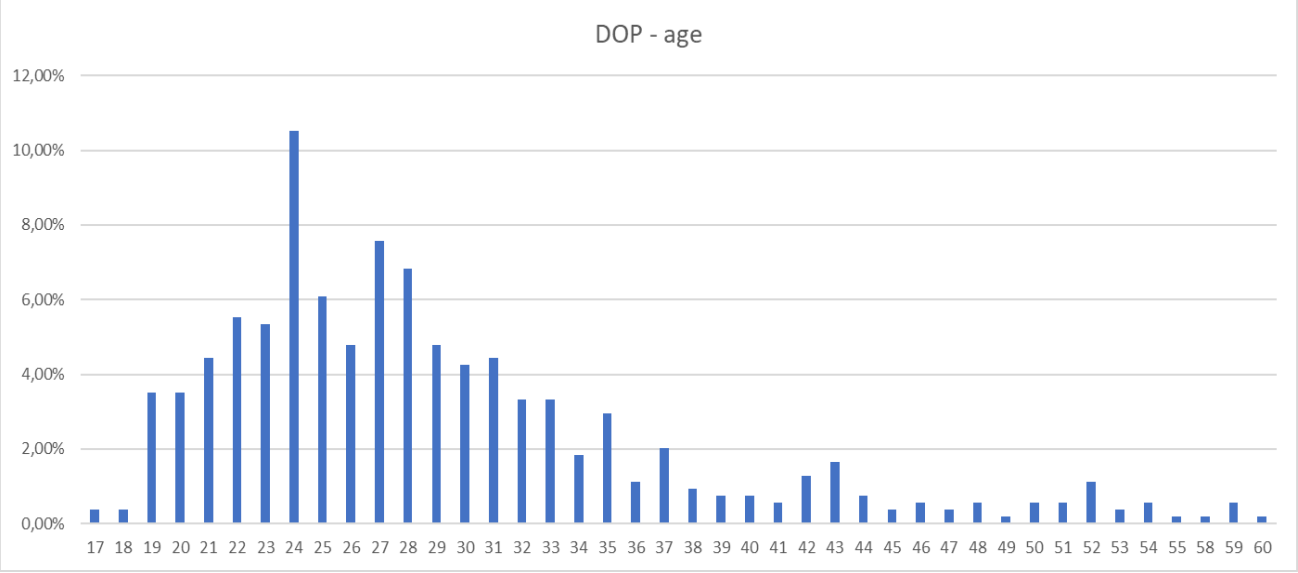


Figure 5: age density distribution

Furthermore, an analysis on the majors faced during the academic courses has been launched; so it comes to the outcomes deriving from the question about the kind of subject studied during university classes while involved into the startup's entrepreneurial activities. Such kind of record resulted in 227 total responses, nearly amounting to the totality of who answered to be student at the previous question, that is as much as 234.

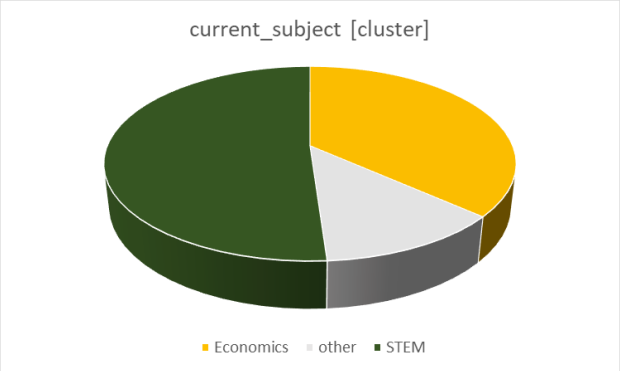


Figure 6: currently attended course

The results were clustered into three macro categories and are showed in Figure 6. There is a certain degree of polarization towards STEM field, which counts for 51% of the whole pool. After, economic studies emerge, weighting for 37% about. Finally we find the residual category, including fashion industry, agrarian techniques, art, media and communication, law, political science and literature. Yet, it was asked whether the entrepreneurs had taken some courses treating of specific topics, such as entrepreneurial education as well as economics and management.

What emerged is that an unexpected number of participants was engaged (or had been engaged) in several types of courses external to InnoVentureLab, always talking about entrepreneurial arguments and economic themes. In particular, referring to the whole pool of 542 individuals, just few people stated to not have interests involved in such kind of classes. Looking at external courses treating about entrepreneurial methods and tools, seven people are identified as blanks (i.e. they did not answer the corresponding question), while as many as 205 entrepreneurs (about 38% of the totality) already took (or were taking) entrepreneurial education (e.g. business model canvas, minimum viable product usage, customer analysis, feedback exchange tools, and so on).

Instead, watching at more traditional courses - that means referring to lessons on economic insights and managerial concepts - the number was even higher. The results are shown in Figure 7, where the two diverse categories are proposed: the two sub-sets are separately splitted, and the belonging to one sub-set is represented as boolean value. The value 1 stands for event manifestation, otherwise zero value indicates absence of expression in that dimension. Reading the chart, as many as 346 people (64% of the whole) affirmed to have received education about management means and economic knowledge (e.g., macro-economic theory, micro-economic theory, corporate finance, game theory, general financial education, stocks market, and so forth).

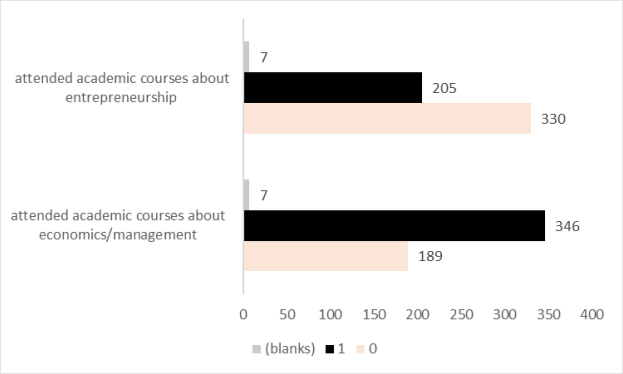


Figure 7: distribution among external courses

At every step of the program progress and for each startup, the research assistants are requested to ask entrepreneurs for another interesting dimension: the amount of hours dedicated to the startup activities, during just a week and referred to every single team member. The outcome is displayed in Figure 8, where a probability distribution is plotted. Please note that, due to scale issues, the second dimension (i.e. percentile value at each abscissa level) is measured on the second axis, located on the right in the graph.

The density distribution clearly identifies the value 10 as modal one, anyway the overall pattern is less polarized than that observed for other dimensions (e.g. seniority distribution). The second mode is in correspondence of twenty hours per week (per member), equivalent to almost 3 hours per day. The overview allowed to observe heterogenous distribution of the 542 entrepreneurs along such variable, and this is due to other potential commitments (e.g., further work activities, university, sons/daughters, chance of separating entrepreneurial tasks among team members, pandemic emergency, lifestyle, and so on). However, majority of people is concentrated on left side of the distribution. Indeed, the 50th percentile is quickly reached: it is individuated just before the modal value, namely where is the value 8, that corresponds to the commitment of a few more than 1 hour per day for each team member.

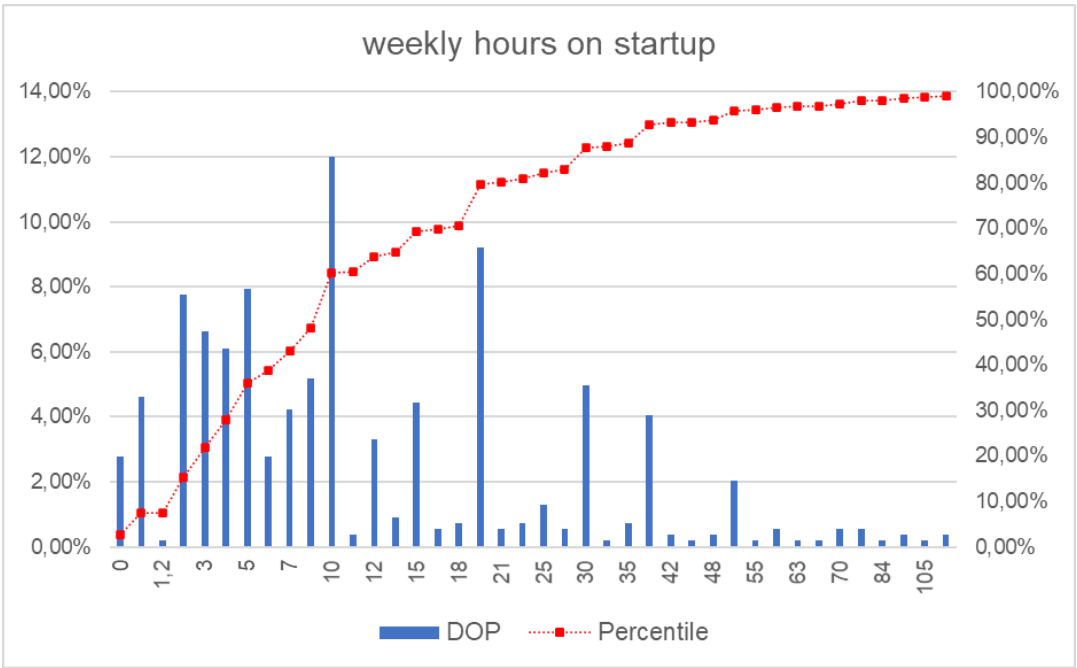


Figure 8: weekly commitment per member

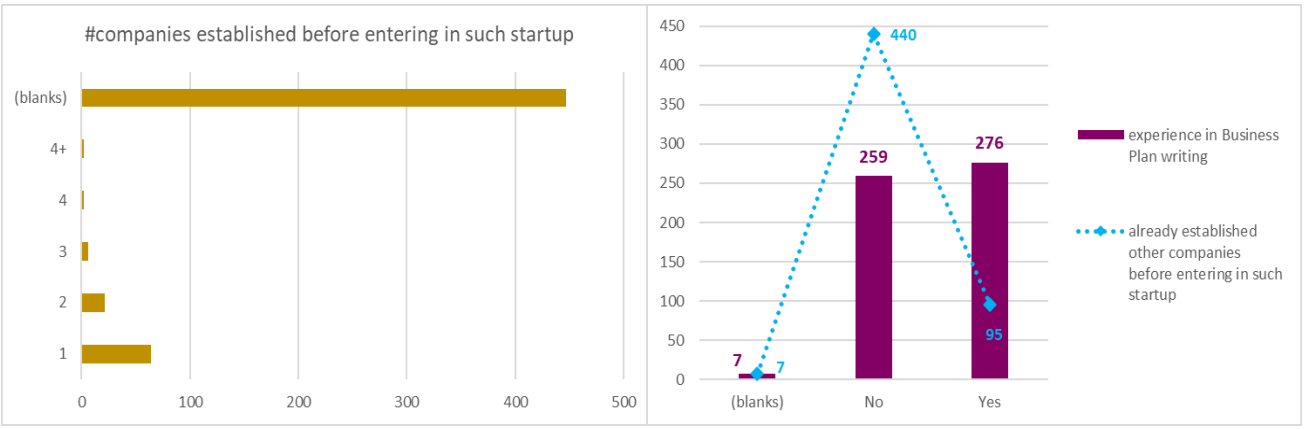


Figure 9: number of companies established before pursuing the startup venture (left)

Figure 10: boolean variables about prior entrepreneurial experiences (right)

Figure 11: years of work experience declared by each team member

Figure 12: years of work experience into the same industry of startup declared by each team member

Figure 13: number of industries in which experience is cultivated

Figure 14: working experience years in role of corporate executive

When focusing on previous experiences declared by participants, it is possible to view Figure 9 and 10: in the second one, two boolean dimensions are displayed in order to indicate how many people already experienced Business Plan writing (276 of 542, about 51%) and venture establishing (95 of 542, about 18%). In addition, in a set of charts ranging from Figure 11 up to Figure 14, the density distributions expressed in absolute values are shown about four different variables. For graphic cleanliness and clarity about numbers, the blank values are not drawn since they are numerous especially into the Figures 12-14, in which they assume hundred order of magnitude, making difficult to read the values reached by the variables of interest. In all of the four scenarios, the modal value corresponds to a very low number (two times is 0, two times is 1), with an overall tendency of the curves toward the left side. Please note that the third variable (number of industries in which experience has been done) is an artificial variable, created by counting for each individual the number of sectors indicated into the answers rather than looking at the nature of such sectors, so that the aim is measuring heterogeneity in prior experience, and flexibility degree achieved thanks to the previous work activities. It is surprising the amount of years in work experience with role of executive: if compared only to who gave answer (135 of 542 people), the percentage of those having at least 5 years of experience as corporate executive is near to 30%.

During the formation of sample and sub-groups of treatment, control and pure control, the progress status achieved by the team was taken into consideration for the class assignment, since the research team considered it as discriminant and potential control variable. In Figure 15 the presence of each progress phase is displayed: for the most part (201) teams stayed into the first phase at zero time, that signalled belonging to the analysis step (i.e. survey and interview to customers were still in progress, website yet did not exist as well as landing page or prototype).

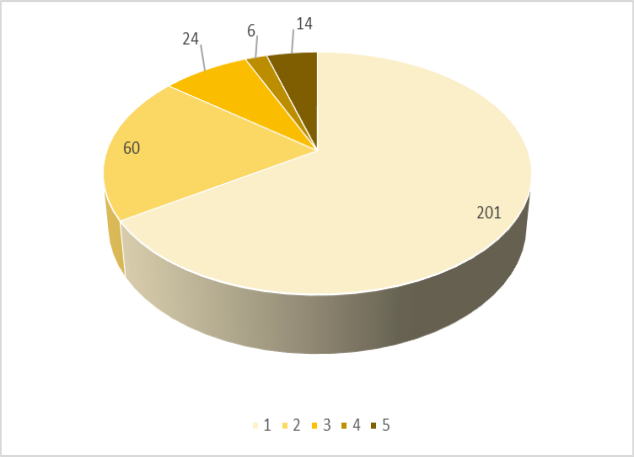


Figure 15: progress phase

The other phases stand for: 2) a product basic version existed, 3) the prototype had being tested toward the client, 4) the offering worked while incomes had not yet been generated, 5) the revenues had started to arrive. Instead in Figure 16 are reported the other - to be meant as in addition to the commitment dedicated on startup workload - commitments declared by each of the 542 participants at the program starting: it is curious to note that only the lowest percentage is represented by people with full-time interest on startup activity, while almost the half of respondents worked while involved into the entrepreneurial tasks.

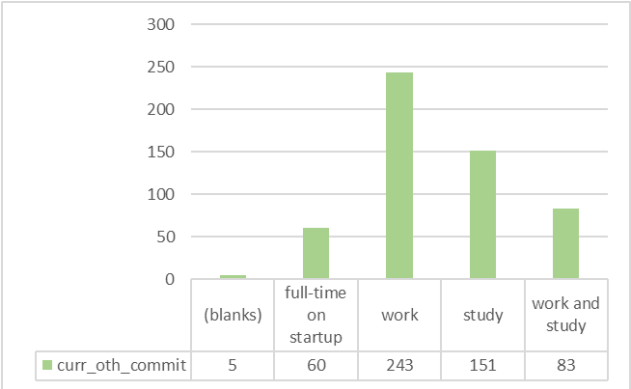


Figure 16: current other commitment

Looking at the studies attended while working for the startup, as many as 233 individuals answered to follow academic courses during the examined period; in particular, the range in which fluctuate the several types of university levels is wide and composed as showed in Figure 17. It appears very popular the choice of beginning an entrepreneurial venture in the same period corresponding to bachelor studies, maybe due to incentives deriving from the new university experience. The ones studying in a doctorate course counted only for five items, that is just 2% out of the total.

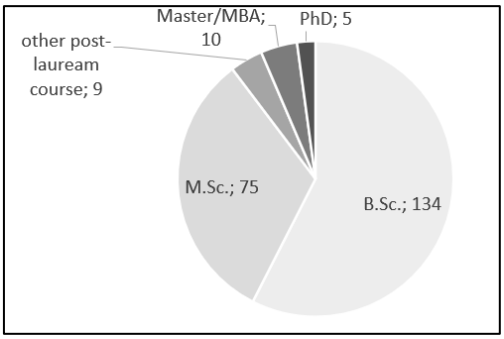


Figure 17: academic level

Successively, a more inclusive indicator was created in order to get a complete framework about the academic levels: the new variable (please view it in Table 1) measured the maximum academic level reached throughout the entire lifespan, so including both the highest study title obtained before starting the program and the current attended course.

Table 1: maximum academic level

Academic_lvl_corrected				
B.Sc.				105
M.Sc.				105
Master				88
nothing				84
PhD				21
studying B.Sc.				127
studying M.Sc.				6
studying Master/MBA				5
studying other post-lauream course				1
				542
Academic_lvl_corrected (years codification)				
Average	*Max*	*Min*	*SD*	*VAR*
1,8672	4,0000	0,0000	1,1715	1,3723

Into the second part of Table 1, it is viewable the split which reports the numerical main descriptive statistics of such variable, which is treated as codification from categorical items to numbers, with the aim of computing finite quantitative values as those shown above. In addition, in Table 2 a statistical description is proposed again: this time, is referred to the psychological variables which in phase of preliminary experiment design were considered useful to be analyzed, in view of potential correlations with decision-making approach. So, they have been quantified and here are presented the typical statistical properties: mean value, maximum and minimum limits (so that it is possible to extract even the range), standard deviation and then variance.

REP boolean: Yes & No	Variable	Average	Max	Min	SD	VAR
I will found a firm in order to	become rich	3,9021	7,0000	1,0000	1,6591	2,7527
	move up into the business world	4,1563	7,0000	1,0000	1,7804	3,1699
	solve a specific problem faced by people with which I strongly identify	5,6008	7,0000	1,0000	1,5500	2,4026
	have a proactive role in shaping the activities of people with which I strongly identify	5,3710	7,0000	1,0000	1,5781	2,4904
	solve a social problem which private firms are not usually able to face	5,4840	7,0000	1,0000	1,6737	2,8012
	have a proactive role in changing the way by which the world acts	6,0038	7,0000	1,0000	1,3161	1,7321
In role of founder, it will be very important for me to	manage my firm basing on robust management practices	5,9190	7,0000	2,0000	1,0916	1,1915
	deeply analyze financial prospective of my business	5,9473	7,0000	1,0000	1,0820	1,1708
	supply offering useful to people with which I strongly identify	5,8343	7,0000	1,0000	1,4112	1,9914
	show my customers that I agree with their opinions, interests and values	5,8079	7,0000	1,0000	1,3034	1,6989
	be highly conscientious world citizen	6,0188	7,0000	1,0000	1,2330	1,5204
	make the world a better place	6,1601	7,0000	1,0000	1,1859	1,4064
When I will handle my corporate, it will be very important to	focus on what my firm can obtain if compared with competitors	5,5292	7,0000	1,0000	1,2858	1,6534
	establish a strong competitive advantage on competitors	5,7740	7,0000	1,0000	1,2641	1,5979
	focus on people with which I strongly identify	5,1224	7,0000	1,0000	1,5859	2,5152
	support people with which I strongly identify	5,1186	7,0000	1,0000	1,5945	2,5425
	focus on what my firm can do for social welfare	6,0094	7,0000	1,0000	1,1598	1,3452
	persuade others that private firms are able to face social problems like those challenged by my firm	5,4068	7,0000	1,0000	1,5674	2,4569
psychological dimensions	SELF ESTEEM	4,4934	7,0000	1,0000	1,2121	1,4693
	RISK APPETITE	5,5521	7,0000	2,2500	0,9178	0,8423
	NOVELTY	4,8793	7,0000	1,3333	1,1582	1,3415
	PLANNER	5,9165	7,0000	1,0000	0,9484	0,8995
	LEARNING GOAL ORIENTATION	6,1308	7,0000	1,0000	0,7875	0,6201
	PERFORMANCE AVOID ORIENTATION	4,3990	7,0000	1,0000	1,3924	1,9388
	PERFORMANCE GOAL ORIENTATION	2,5637	7,0000	1,0000	1,2784	1,6344
	TEAM BUILDING	5,6059	8,0000	1,0000	1,9432	3,7759

Table 2: descriptive statistics

3.1 Team level aggregation and database creation

The variables illustrated within the above chapter have been deeply analysed in order to generate a new set of dimensions at team level, starting from the initial dataset. First of all, the team leaders (i.e., representative, spokesperson) were used as reference fellow in considering some categorical variables, since they offer a good idea of which are the aptitudes and practices characterizing the whole startup.

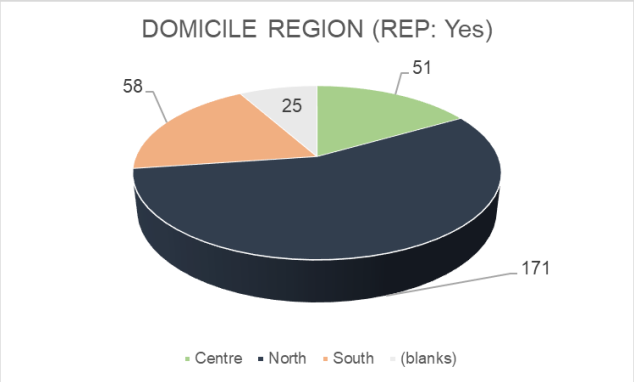


Figure 18: team leaders' origin

The geographical provenience of each team representative is tracked in Figure 18, revealing that individuals mostly come from north of Italy, while the ones from south and centre are nearly in same proportion. This enough heterogeneous geographical composition has been made possible thanks to the fact that the entire program is delivered through online channels (due to pandemic situation), so avoiding necessary physical presence and travel costs, namely allowing subscriptions from all around the national territory. Yet, to each startup an offering typology has been assigned, according to what declared by the team representative.

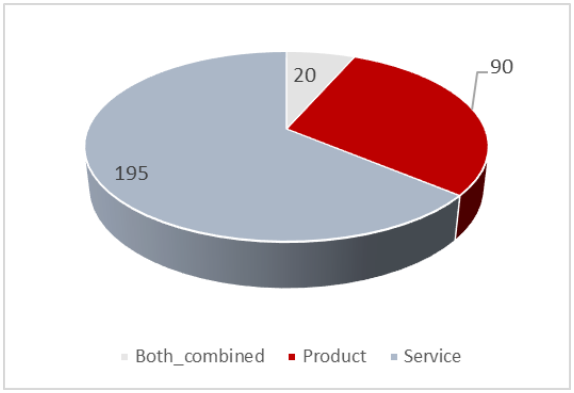


Figure 19: kind of offering

In the pie chart above, it appears how the startups delivering services are the most numerous, amounting to around 64% of the totality. The belonging to one or another of such categories is useful as control variable, since we expect to differentiate the decision-making processes according to what is the main offering proposed by entrepreneurial team. Meanwhile, a core dimension employed for the regression analysis is the artificial variable named as *internal network*, since it measures the extent to which cohesion and strong network among team members are detected.

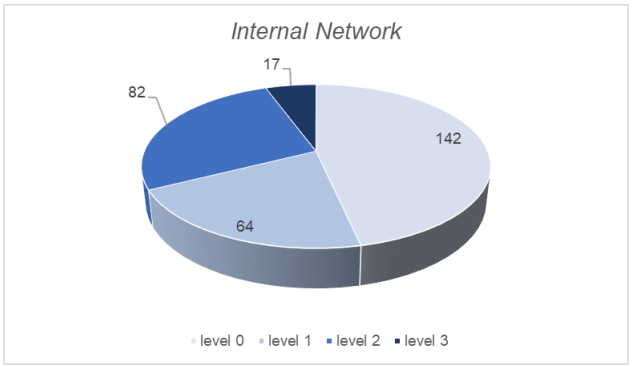


Figure 20: internal network

Such dimension was shaped by looking at three different boolean variables - that were: 1) *did you attend, even if in different periods, the same university of at least one of the other team members?*; 2) *did you work, even if in different periods, in the same corporate where at least one of the other team members worked?*; 3) *before working on this business idea, did you have work or study collaborations with another team member?* – with the aim of obtaining a quantitative indicator of ties preexisting among members (i.e. previously to the startup foundation). These questions have been considered only when asked to the team representative, in order to eliminate redundance and double bonds or worthless complications due to matching activities. When there is absence of all the three sub-dimensions, the resulting internal network level is zero. Consequently, if only one boolean is equal to one, it means the event manifestation is anyway observed, so that the final level becomes 1. After, if two boolean items return positive outcomes then the resulting level is 2, so that whether all the three values display 1 then the level is 3. The consequent variable intensity is plotted in Figure 20 by using diverse shades of blue, and increasing colour intensity as level magnitude arises: the overall intensity along such dimension is low, indeed 46% of the total teams registered minimum level, whereas only the 6% falls into the maximum one. Figure 21 permits to have a complete overview on the distribution of average age of the teams, expressed in absolute terms and not in percentages, where the mean value is computed by applying arithmetic average on everyone belonging to team. The curve is not particularly switched toward the left side, signalling quite heterogeneity along such parameter. At half of the area subtended under the curve (50th percentile), it comes to a few less than 28 years old; that is an expected result, given that the most of participants are young and declared less than thirty years, so that outcome appears to be consistent with the previous statistics.

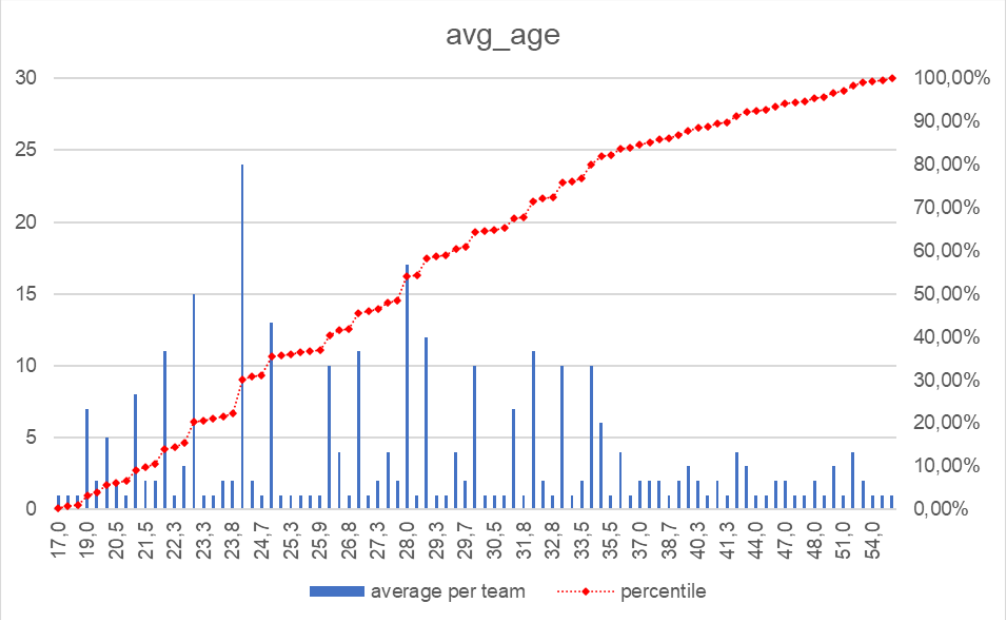


Figure 21: age distribution among teams

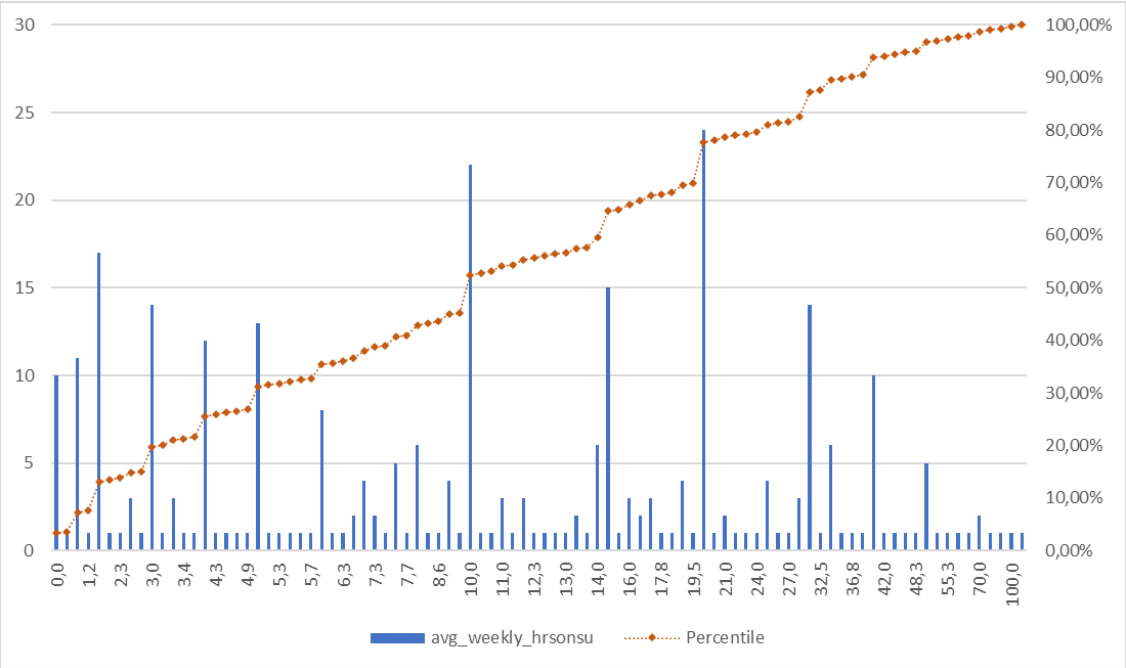


Figure 22: average weekly hours of commitment per member

Proceeding with aggregation of single data at team level, Figure 22 returns the outcomes referring to the commitment invested on startup activities: the range of hours comes from null value until 110 hours a week, equivalent to about 16 hours a day per member. It is important to underline that the total commitment obviously depends on team numerosity, other than the single amount of hours per person. The modal value is around 20 hours per week per member, corresponding to almost three hours per day for each team member.

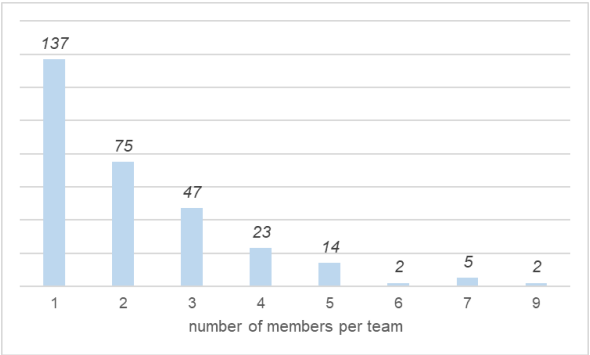
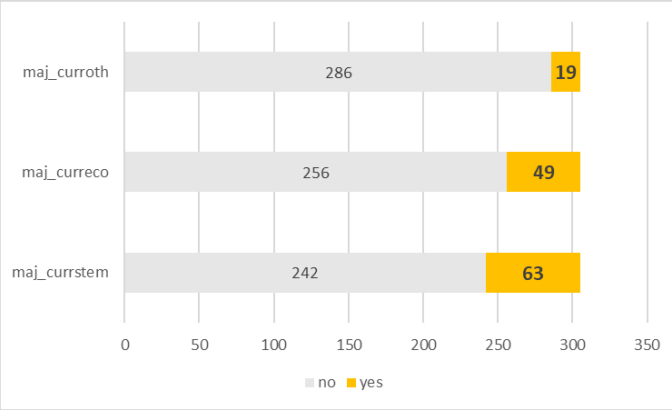


Figure 23: team numerousness

Right about team numerosity, in Figure 23 is displayed the numerousness recorded by every team. Please note that such variable derived from what stated by representative entrepreneur during compilation phase, therefore not taking into consideration the actual answers received. The majority of the sample declared to be involved in unique-person teams (around 45%, 137 of 305 startups), after there are dual teams (~ 25%) and so forth, decreasing in frequency by increasing in numerousness as it was expected: just few ventures consist of more than three people, due to difficulty of finding compatible individuals with which sharing key decisions and strategies. The highest gap, in terms of frequency, is at the turn of 5-members and 6-members groups: the numerosity equal to 5 counts 14 startups, while numerosity equal to 6 fellows accounts for just two persons, equivalent to less than 1% compared to the totality of 305 enrolled teams.



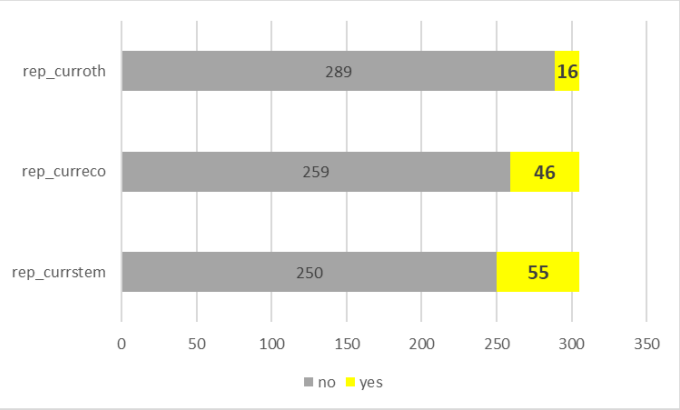


Figure 24: current subject studied by majority

Figure 25: current subject studied by team leader

When it comes to the different majors studied during the classes attended while following the IVL program, it becomes fundamental the creation of three macro-categories in which clustering all the possible facets: STEM (science, technology, engineering and mathematics), economics and other. During the aggregation at team level, two different dimensions were separately analyzed for each startup team: the belonging of the majority within the team (please see Figure 24) and that of the team leader (Figure 25). What emerged is that in both cases the most of participants were STEM students, with a slight advantage over economics students; the gap is slightly more pronounced at majority standpoint. The missing values represent a prominent slice: they account for 174 records in majority counting, while 188 records in representative counting. Remaining into the academic field, but moving towards the level instead of background type, we can look at Figure 26: the density distribution of the average maximum academic level (codification in years) is represented. The mean is computed starting from values ranging between 0 and 4, so that even the resulting mean fluctuates between zero as inferior limit and four as upper limit. It is curious to observe how the modes all locate in correspondence of finite values (i.e. no decimals), that are 0, 1, 2 and 3. Such phenomenon happens because of the numerosity of teams: they are mostly composed of 1 entrepreneur, thus the consequent average outcome belongs to the natural numbers' set. Keeping in mind the codification (PhD=4; B.Sc.=2; InProgress=1; other=0), the level 3 stands for master's degree and similar: right the value 3 is the most frequent, sounding like the average overall maximum academic level is equivalent to master.

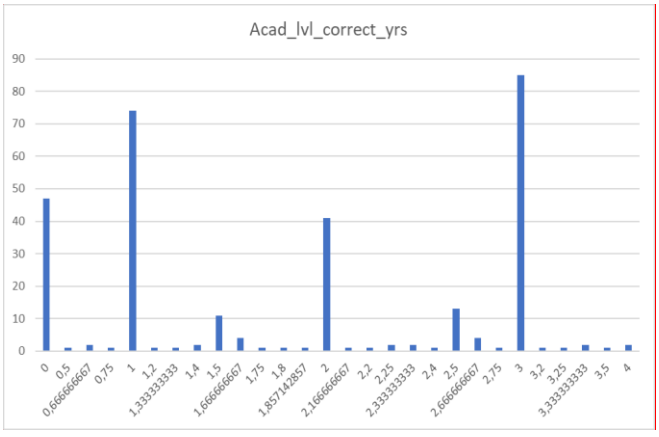


Figure 26: average maximum academic level achieved

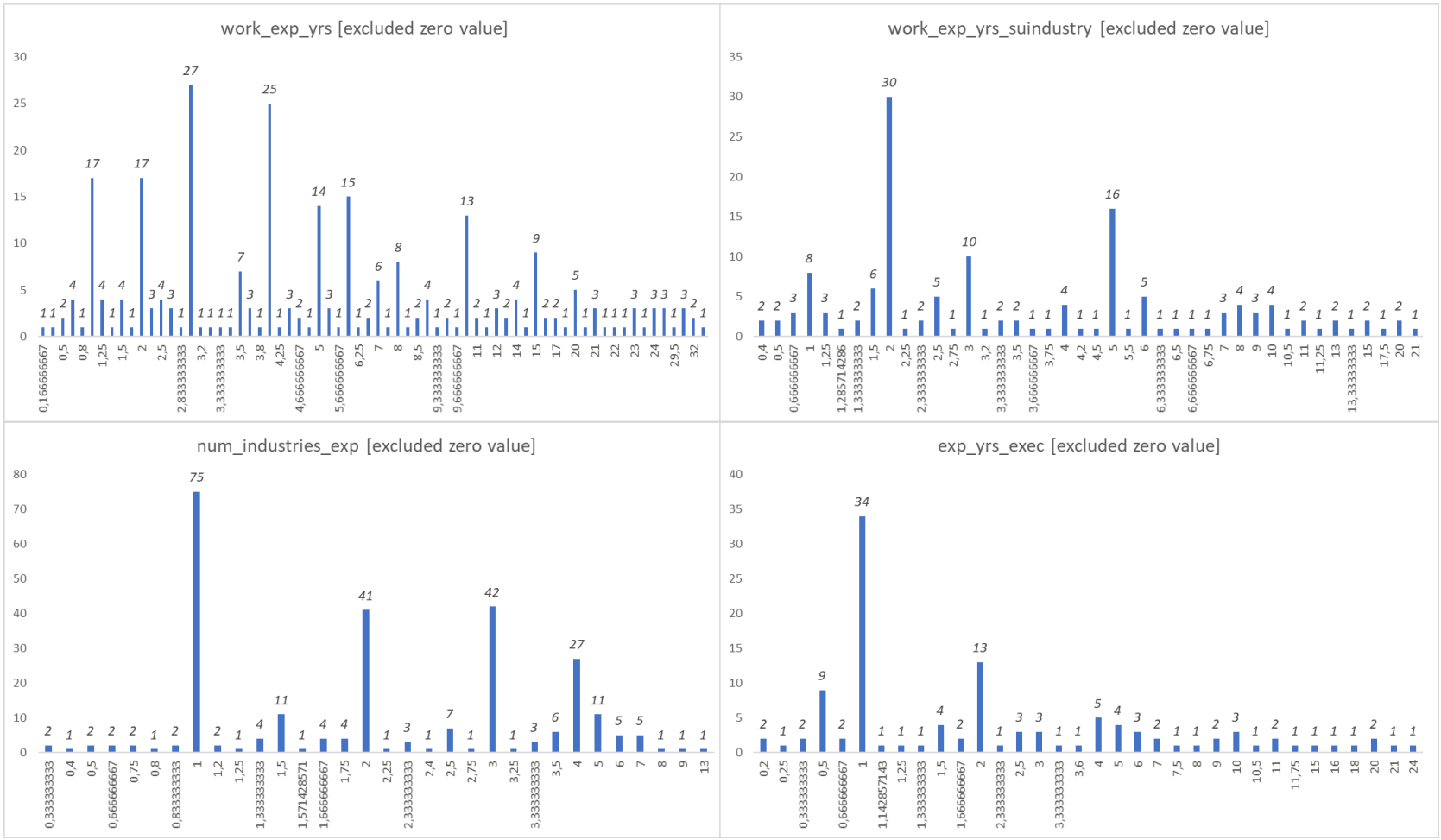


Figure 27: average years of work experience at team level*

Figure 28: average years of work experience within the same industry of startup at team level*

Figure 29: average number of industries in which experience has been cultivated at team level*

Figure 30: average years of experience as corporate executive at team level*

* Value 0 has been not plotted since it gets huge numerosity and therefore causes scale problems in graph visualization, not allowing to well view and appreciate the other lower values

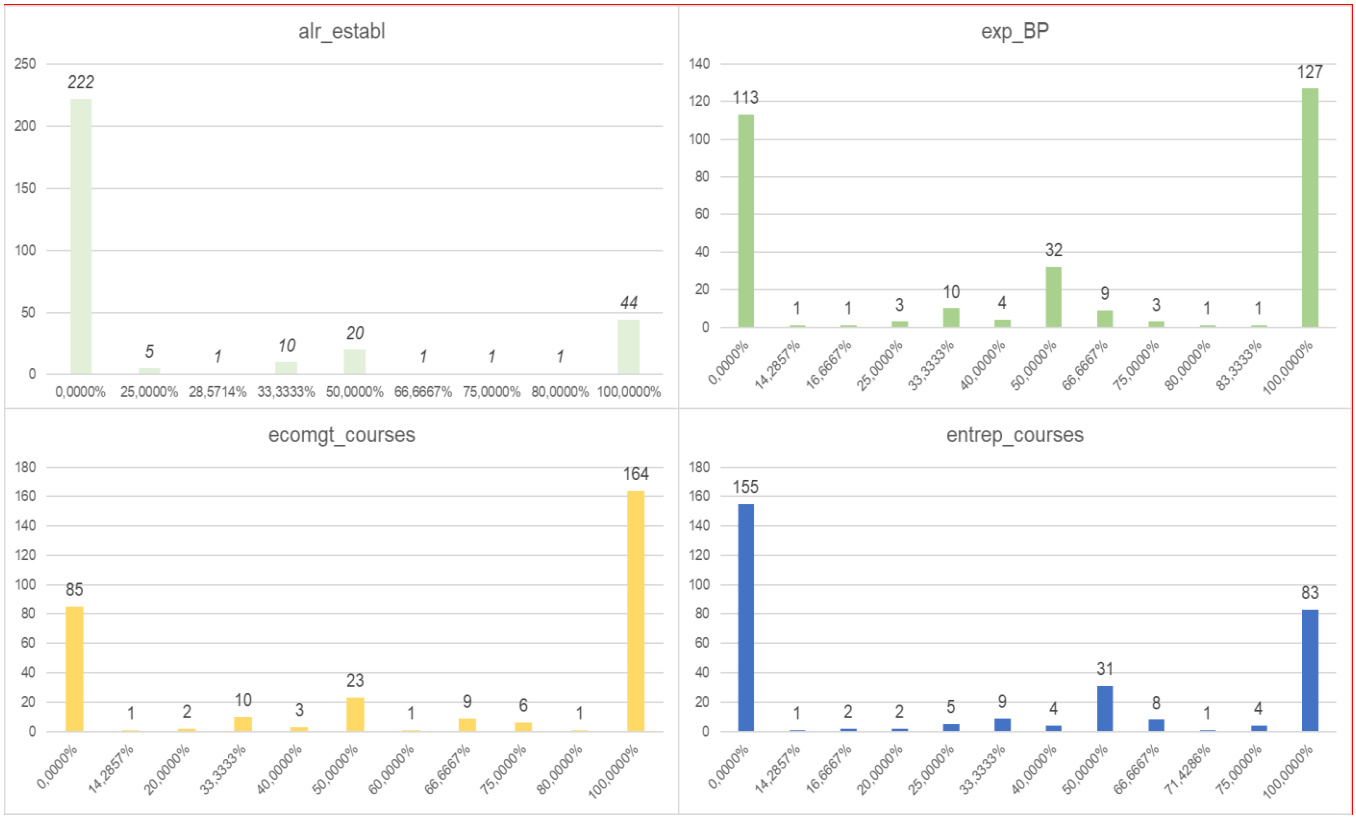


Figure 31: already established other companies before entering the startup team

Figure 32: previous experience in business plan writing

Figure 33: attended other economics and management courses

Figure 34: attended other entrepreneurial courses

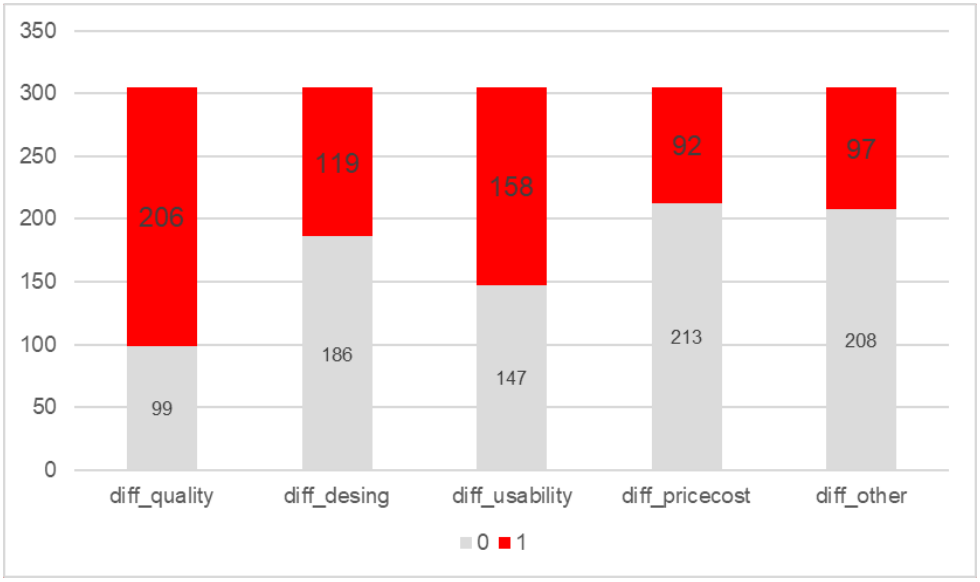


Figure 35: dimension in which the startup differentiates (team leader's perception)

Yet, looking at the variables referred to prior experiences deeply analyzed throughout the above chapter, a further step is done by extending the analysis to team aggregate level: in Figures 27-30 are presented the probability distributions, expressed in terms of absolute values, of four variables already explained in this thesis work. Please note that the trend defined in i) years of work experience, ii) experience in the same sector to which belongs the startup enrolled in IVL and iii) years of prior experience in charge of executive role highlighted low average overall values, since the entire distribution switches towards the left side and the modal value falls always within the left area. The above consideration is ever verified except for a variable: Figure 29 shows that the mode is again on a reduced value (1 sector in which work experience has been done), however all the residual frequencies dispersed through the whole right side of the plotted area, signalling a great number of teams (startups) with high flexibility level - because it was measured as the average number of different industries in which members experienced work tasks (that is, a factor underlying to agile mindset and flexibility when applied to decision-making process).

In Figures 31-34, we can see the original boolean values (even in this case everyone has been already explained in previous chapters) which, at startup level, have been transformed in percentage of event manifestations (% of 1 boolean value) compared to the team total numerousness, so that a quantitative tool can be kept without losing information on the treated dimension. In each graph, the count of each value indicated on abscissa axis must return 305 as final sum, and that is verified in all of the four scenarios. It is relevant noticing that, for all the 4 variables, the two most frequent values are exactly at the antipodes of density distribution: this is true for who already established other companies (222 startups registered 0% of members vs 44 registered 100% of members), who already did business planning (113 vs 127 startups), who took external economics and management courses (85 vs 164 enterprises) and who attended external entrepreneurship courses (155 vs 83 different ventures).

Instead looking at Figure 35: entrepreneurs (representatives are considered as reference because of their more reliable judgement) were asked of which dimensions they believe were the most important within the competitive environment in which they played. The several alternatives are 5, and it is highly interesting the resulting outcome: the differentiating dimension chosen by participants more frequently is quality, in opposition to the less selected, that is price/cost focus. This result reminds of the economic theory, specifically to the discerning between the two more utilized and basic approaches in strategic competition decision-making: differentiation strategy (based on quality, or better to say "perceived quality") versus efficiency setting (made possible thanks to cost destruction and consequently price competition).

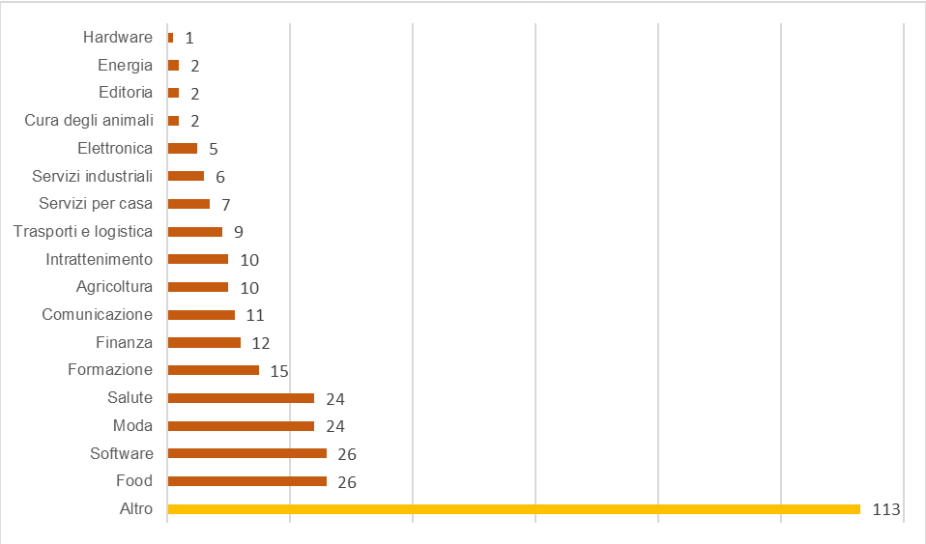


Figure 36: industries to which belongs each startup (N=305)

In conclusion, view in Figure 36: here are showed several industries ordered by increasing frequency, all including at least two teams except for the hardware sector. These are the main types suggested into the survey, with the aim of clustering every possible combination. Obviously, the most populous category is the residual one, which groups all the remanent industries not considered by the pre-setted options: e.g. real estate, healthcare, environment, marketing, automotive, manufacturing, travel and tourism, beauty care, sport, design, photography, sustainability and social network. The sum of the frequencies with which every industry appears is equal to 305, so that the entire sample is present, avoiding lack of information in blanks. Please note that food, software, fashion and health are the most prominent areas in weight, registering large gap if compared to the following ones.

4. Results analysis

Finally it comes to conclusive outcomes. First, please note that as many as nine different regression model have been elaborated, each one splitted for scientificity and effectuation as dependent variable and, in the end, each one has been duplicated for testing in the robustness check models. In Appendix B please view an extract from the correlation matrix used as orienting map: here only the correlation with the dependent variables are displayed - given the elevated numerousness of variables (121x121 matrix) - and a conditional formatting is applied with the aim of highlighting the diverse intensities of correlation. Such matrix has been initially used in order to understand how moving in the large amount of dimensions, by quickly individuating the best relationships between independent variables, as well as between independent and dependent ones. Please note that the variables of interest (i.e. natural levels of scientificity and effectuative approach) have been also

considered in a weighted form, with the weights reported in Table 3. First of all, for each sub-category underlying to the two main variables the standard deviation has been computed among all the record (represented by the 305 startups), as of the reciprocal is immediately available: the total sum of reciprocals is needed as normalizer, so that every single weight is ready (and the sum of weight is 100% as verification). The more the anti-variance is high, the more the sub-category gets relevance in the final weighted mean. Such computation has been done since it could be useful to isolate outliers and distortions due to biased judgements from different research assistants – so when for a certain sub-category the judgement is homogenous among all the variables then a more reliable indicator is expected, seen that it means there was no outliers by neither RA side nor startup side.

As opposite, should the standard deviation being too high for a certain sub-category among the participants, then it would signal that a set of startups registered abnormal values, with ambiguity whether deriving from RA's error or venture performance. Therefore, in the weight row from Table 3 are recorded the values by which the averages are multiplicated in the final weighted mean. However please notice there are no significant differences if compared with the not-weighted values, indeed the statistical results expressed into the regression models do not differ if the weights are included. This is the reason why the weighted dependent variables will not be analyzed in such thesis project, seen that the evidences reached with the not-weighted variables of interest keep the same within the weighted case. Indeed in Appendix B the equivalence is easily readable: the correlation values are around the same number both for weighted and not-weighted scientificity level, as well as for weighted and not-weighted effectuation level.

A further verification is offered by the diverse shades of colours adopted to immediately distinguish the magnitude of correlation: the various types of colours are always coupled, namely every couple of dependent variables – normal/weighted scientific approach and normal/weighted effectuative approach – always shows the same shade of colour (or non-colour if the correlation is not sufficiently high) by getting a similar degree of correlation intensity. Finally a comparison between anti-variance values: only a very slight difference exists between scientific (3,8531) and effectuative (3,9798) approach, thus we can conclude that the variability (standard deviation) observed for the two macro-categories is comparable, in other words no distortions from outliers is expected.

SD	1,077099551	1,189295822	1,597421542	1,350189426	1,394240433	1,112815896	1,540012152	1,16437591	1,504228115	1,101005991
WEIGHT	24,095%	21,822%	16,247%	19,222%	18,614%	22,579%	16,316%	21,579%	16,704%	22,821%
1/SD	0,92841929	0,840833695	0,626008836	0,740636818	0,717236408	0,89862124	0,649345526	0,858829173	0,664792786	0,908260271
	1/SD sum	3,853135046		WEIGHT sum	100,000%	1/SD sum	3,979848996		WEIGHT sum	100,000%
var.	THEORY	HYPOTHESIS	TEST	VALIDATION	DECISION THRESHOLD	BIRD IN HAND	AFFORDABLE LOSS	CRAZY QUILT	LEMONADE	PILOT PLANE

Table 3: weighted scientific and effectuative natural levels

4.1 Preliminary evaluations

The regressions have been chosen and launched by using the numbers emerged in the correlation matrix (Appendix B) as reference, with the objective of maximizing the correlations with the dependent variables while avoiding multicollinearity among independent variables, which would generate ambiguity in interpreting outcomes and distinguishing effects, other than penalizing the coefficients' statistical relevance and the adjustment goodness measures. In Appendix C are shown – for each model and for each variable – the significance and the verse of all the relevant statistical relationships. Please note that every independent variable keeps a steady verse throughout all the regression models, so that consistence among them appears to be confirmed. Firstly, deserves to be mentioned the extremely high correlation between the two dependent variables. Indeed, as displayed in Figure 37, it is possible to observe how the variables of interest follow almost a linear function as kind of dependence, so underlined the high level of collinearity which can be explained with the following statement: the analysis treated in this thesis project only considers the initial phases of the IVL experiment.

In other words have been included exclusively the data available at time zero before any type of lesson and technical suggestion by the instructors. This is the reason why the levels of scientificity and effectuation can be considered as natural, seen that they should be innate in the individual aptitude and not influenced by program's contents and interaction insights. Thus, obviously the natural levels of scientific and effectuative orientation were expected to be similar before the program beginning. In addition, we must consider that a sort of learning economies exist among the research assistants, since the judgements they give may become more and more accurate and not biased by better knowing the participants, as well as by doing interviews and assimilating the theoretical concepts.

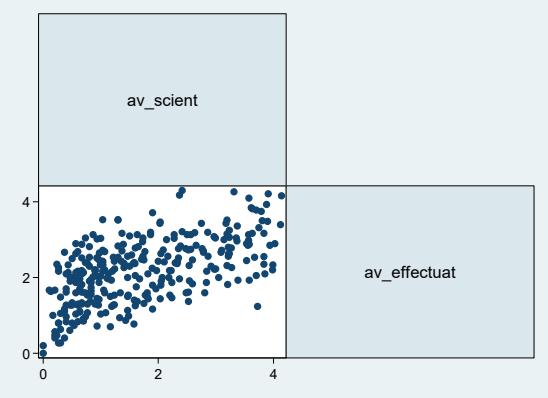


Figure 37: scientificity-effectuation relationship well rounded by linear function

Instead, looking at the split of the dependent variables, as described into the previous chapters we can discern 10 sub-variables divided in 5 for scientificity and 5 for effectuation. It is interesting to highlight the dependences emerging between the components which composed the main variables of interest. In Table 4 the levels of correlation measured through the Pearson coefficients are presented, and then confirmed by the graphs illustrated in Appendix D: each kind of colour indicates a diverse range of intensity, in order to quickly individuate the higher and lower correlations between all the sub-variables.

	av_scientth	av_scienthp	av_scienttest	av_scientvalid	av_scientdecthresh	av_effectuatbird	av_effectuatloss	av_effectuatquilt	av_effectuatlemon	av_effectuatpilot
av_scientth	1									
av_scienthp	0,704284422	1								
av_scienttest	0,506565443	0,657486364	1							
av_scientvalid	0,491528959	0,652540558	0,855542662	1						
av_scientdecthresh	0,413211211	0,534501949	0,647792536	0,766889971	1					
av_effectuatbird	0,457554298	0,389177635	0,344188954	0,307036275	0,221606057	1				
av_effectuatloss	0,306015639	0,23003089	0,249409684	0,244854663	0,187059711	0,258145972	1			
av_effectuatquilt	0,434946493	0,406066701	0,423856642	0,43514066	0,454217005	0,319859374	0,245655035	1		
av_effectuatlemon	0,36855569	0,346920236	0,326551518	0,376760538	0,299710665	0,27209254	0,27391814	0,366587314	1	
av_effectuatpilot	0,447303146	0,364339006	0,219727987	0,271142283	0,263063843	0,266956585	0,284346441	0,317680826	0,256306932	1

Table 4: Pearson coefficients computed for all the sub-variables of interest

The most elevated correlations (bordeaux zone) show in the scientific approach paradigm: the validation (*av_scientvalid*) and test (*av_scienttest*) components registered the highest value which amounts to 0.8555, whereas the second one correlates appropriate threshold during the major decisions (*av_scientdecthresh*) with the validation component and is equal to 0.7669 – the result is in line with what expected since the validation phase usually comes after the test step but before the core decisional moment, so that a sequential connection exists along with the conceptual correlation between the different phases of a same cognitive process. Yet, more in general all the sub-variables underlying to the scientificity world appear to be highly correlated among them, and such evidence is no longer true if we watch the effectuative approach paradigm. There, the Pearson coefficients are deeply lower and it is surprising that such sub-variables recorded more correlation with the scientificity components than among themselves.

The lowest value in Table 4 is in correspondence of scientific decisional threshold and loss orientation (*av_effectuatloss*) by registering an intensity equal to 0.1871 – here we need to remember that the scientific threshold measures the extent to which people took decision by using solid criteria, and it further assesses the criterion's reliability and consistency. Such point perhaps could explain the low correlation with the loss variable: the loss aversion/appetite measures also whether the individual is oriented or not towards the risk, rather than the appropriate criterion chosen for taking orientation. So that an entrepreneur might be weak in initial economic investment and when evaluating how much is willing to loose, meanwhile being largely scientific and able to select the best criteria during the core decisional moments. After, the second lower value in Table 4 is between pilot effectuative aptitude (*av_effectuatpilot*) and scientific test phase, with a coefficient of 0.2197: this can be justified by the fact that the pilot plane feature is associated with who prefers to execute (rather than overthinking) and control what is well known by not waiting for others' predictions or possible future events. Such characteristic seems not to be related in any way to the scientific capacity of testing hypotheses, neither with positive verse nor with negative relationship.

4.2 Regression presentation

In this paragraph the nine different regression models will be presented and discussed. Firstly, the model 5.b displayed in Figures 38 and 39 represents the best fit among all those that have been launched: the adjustment goodness measures are the highest ones, indeed the R-squared parameter is 0.4296 and 0.5433 respectively when the dependent variable is natural level of scientificity and effectuation; in other words, this is the model getting the highest degree of variance explained by the considered variables. Furthermore the Root MSE (Mean Squared Error), that is a value to keep the lowest as possible since indicates the residual error dispersion (where error is difference between actual and predicted value), is minimized by assuming value respectively equal to about 0.939 and 0.636 - thus we can conclude that 5.b is the model able to explain the greatest quantity of variance while recording the minimum error observed in this analysis.

Looking at the independent variables, the industry to which the startups belong appears as statistically significant: taking into consideration the poor numerousness of the most of industries, it is appropriate to focus on the more populated industries. For instance the software sector, having numerousness of 26 startups, shows negative statistical correlation with the effectuation natural level in the model 5.b and at the maximum level of significance ($p<0.01$), whereas no relationship emerged with the scientificity natural degree. Yet, the geographical origin affects the dependent variables in such model; in particular, belonging to regions of the south is negatively correlated with the effectuative approach, even if the significance is enough low ($p<0.1$). The numerousness of the startups is statistically relevant too, given that presents positive and strong ($p<0.01$) coefficient into the relationship with the effectuative approach. After, also the commitment invested on the startup work is a core factor in the model 5.b: for each startup the average number of weekly hours employed by each member is positively and highly correlated with both scientific and effectuative approach's natural levels. In addition, it is relevant that the boolean utilized for the phase 2 of the startup progress registered highly significant coefficient: within the model 5.b it is positively correlated with both scientificity and effectuation, and always reporting the greatest level of significance ($p<0.01$). Please note that the omitted boolean is the one referring to the startup phase number 1, so that the results highlighting positive correlation for all the following steps are in line with what expected: indeed the 2-5 steps always show positive correlation with the natural level of effectuative approach, while this is not always true for the natural level of scientific method (i.e. in phases 3 and 4). This outcome would be explained by the fact that not all the entrepreneurs in advanced development phase are there thanks to particular entrepreneurial education or structured insights, there it looks like that being a good entrepreneur is not always aligned with acting like a scientist, but seems being always associated with better abilities of execution and control on which bases the effectuative paradigm.

Variable	active
suind_agric	2.857e-16
suind_commun	-3.982e-16
suind_anim~e	-3.877e-16
suind_publ~g	1.180e-15***
suind_elec~o	2.031e-16
suind_energ	-7.885e-16**
suind_fina~e	-8.450e-18
suind_food	1.679e-16
suind_educ	6.752e-16**
suind_hardw	1.357e-15***
suind_entert	-3.096e-17
suind_fash	-2.794e-17
suind_health	-9.605e-17
suind_indu~v	-4.419e-16
suind_home~v	2.184e-16
suind_sw	6.788e-17
suind_tran~g	-1.432e-16
center	8.587e-17
south	-1.853e-16
su_numer	.09274864
av_weekly_~r	.01182135**
su_ph2	.59358984***
su_ph3	.40677752
su_ph4	-.97948741
su_ph5	.55122269*
serv_offer	.41147434***
bothcomb_o~r	.30513705
av_aclvlyr~t	.16471304
av_numindu~p	.06135024
alr_establ	.02477965
av_numestabl	.11406647
exp_bp	-.11327496
ecomgt_crs	.18326464
entrep_crs	.1015884
av_horiz2	.02569428
intern_netw	.14847066*
diff_usab	.08233434
av_rlvncoth	.0116613
av_pgo	-.05217696
av_perfori~t	.00218348
av_solveid~t	-.00886831
av_shapeid~t	.0453236
av_focusid~t	.06448047
av_supident	-.03308528
av_teambuild	-.02605777
bu_gender	-.32758897
bu_age	1.3621023**
bu_region	.2571175
bu_othcom	-.21173095
bu_curstude	.33979008
bu_expbp	-.51889844
bu_alrestabl	.10690898
bsc_maj	-.00701052
msc_maj	-.26789864
master_maj	-.02486006
nothing_maj	.18735521
phd_maj	.2828529
bsc_ing_maj	.17795785
msc_ing_maj	.94874872*
master_ing~j	-.5378596
postlaur_i~j	(omitted)
_cons	-.22591505

```
Linear regression                               Number of obs =     298
                                                F( 41,   237) =       .
                                                Prob > F      =       .
                                                R-squared     =  0.4296
                                                Root MSE      =  .93998
```

legend: * p<.1; ** p<.05; *** p<.01

.

Figure 38: model 5.b – scientificity

Variable	active
suind_agric	-3.517e-17
suind_commun	-2.268e-16
suind_anim~e	-1.099e-15***
suind_publ~g	-1.059e-16
suind_elec~o	-3.328e-16
suind_energ	-3.654e-16**
suind_fina~e	1.561e-16
suind_food	-5.154e-17
suind_educ	-9.863e-17
suind_hardw	1.004e-15***
suind_entert	-1.548e-16
suind_fash	-8.081e-17
suind_health	-1.224e-17
suind_indu~v	2.178e-16
suind_home~v	-3.626e-17
suind_sw	-3.975e-16***
suind_tran~g	-1.833e-16
center	-1.337e-16
south	-1.963e-16*
su_numer	.11132***
av_weekly_~r	.00692677***
su_ph2	.72404926***
su_ph3	.44822506***
su_ph4	.66400026*
su_ph5	1.0341203***
serv_offer	.10247066
bothcomb_o~r	.1829927
av_aclvlyr~t	.17735883
av_numindu~p	.05269582*
alr_establ	.60948783***
av_numestabl	-.33489641***
exp_bp	.11999032
ecomgt_crs	.08627333
entrep_crs	-.07449059
av_horiz2	.0121409
intern_netw	.10990198**
diff_usab	-.03579264
av_rlvncoth	.01280233
av_pgo	.01976253
av_perfori~t	-.06793628*
av_solveid~t	-.02096298
av_shapeid~t	.04979975
av_focusid~t	.0106193
av_supident	.05332908
av_teambuild	-.01692533
bu_gender	.16288596
bu_age	.40400685
bu_region	.15148849
bu_othcom	-.27957889
bu_curstude	.67807369*
bu_expbp	.04137326
bu_alrestabl	-.2694513
bsc_maj	-.19173343
msc_maj	-.15943107
master_maj	-.25989651
nothing_maj	.08845796
phd_maj	-.70497413*
bsc_ing_maj	-.00081919
msc_ing_maj	.73890409***
master_ing~j	-.61344003
postlaur_i~j	(omitted)
_cons	1.0122864***

legend: * p<.1; ** p<.05; *** p<.01

```
Linear regression                               Number of obs =     298
                                                F( 41,   237) =       .
                                                Prob > F      =       .
                                                R-squared     =  0.5433
                                                Root MSE      =  .63583
```

.

Figure 39: model 5.b – effectuation

Another interesting point emerging from model 5.b is about the control variable of offering kind: taking into consideration that the omitted boolean is the offering like product, the startups selling services (rather than products) resulted to be extremely more scientific (greatest level of significance), but no relationship is found with the effectuative approach.

The artificial variable created to measure the number of diverse industries in which the founders have had experience is statistically relevant too. Furthermore, also the experience deriving from previous tasks involved in venture establishment (i.e. boolean indicating whether the individual has already established other firms) results to be largely ($p<0.01$) and positively (verse +) correlated with the innate effectuative approach (but not with the scientific one), signalling that more pragmatic education and insight can be effectively useful in improving the abilities related to control and execution. An interesting side effect is that another experience proxy, namely the number of firms previously established by each participant, is strongly ($p<0.01$) but negatively related to the effectuative nature; the phenomenon can be due to the poor numerosity of such set, given that the records in *av_numestabl* variable are mostly (>90%) blank values.

The *av_pao* dimension, that describes the Performance Avoid Orientation, is negatively correlated into the model 3.b; so that the aggregated variable *av_perforient*, computed as simple sum of PAO and Performance Goal Orientation, presents again a negative correlation coefficient with the effectuation method, even if the significance degree is low ($p<0.1$) because probably mitigated by the PGO effect. Finally it comes to the heterogeneity indicators: in 5.b model only the Blau's index referred to the student quality (*bu_curstude*) presents statistical relevance – but however minimal ($p<0.1$) – since it is positively related to the effectuative approach but not to the scientific one. Therefore it seems that the diversity in terms of students' presence within the team positively affects the group abilities of execution and control. The right mix of current students and more experienced people lead to merge practical insights and technical education, so as a more pragmatic and empirical approach can be supported by solid academic insight and deep knowledge about the business/technology topic. By the way, please consider that such result is not completely reliable since the Blau's index here recorded just a few values not equal to zero (36 out of 305, around 12%). Finally, the boolean indicating whether the team majority belongs to a B.Sc. class is in alert area: indeed *bsc_maj* is negatively correlated with effectuation at an almost relevant significance degree ($0.1<p<0.15$). This is in line with what known in the theory: the effectuation method is what Berkeley's (San Francisco, US California) professors teach in their entrepreneurship lessons, a highly recognized and appreciated approach diffused in a number of prestigious academic structures. It is something deriving from experience and execution, trial-and-error processes as well as innate aptitudes, thus belonging to the lowest academic level (i.e. Bachelor degree) generally signals for low seniority and poor empirical experience, then suggesting for inferior capabilities of execution, network, flexibility and control.

Linear regression

Number of obs	305
F(10, 294)	6.76
Prob > F	0.0000
R-squared	0.1551
Root MSE	1.0398

av_scient	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
fem_oneplus	.0330304	.1457186	0.23	0.821	-.2537534	.3198141
maj_currstem	.067323	.1754227	0.38	0.701	-.2779204	.4125664
maj_curreco	.2011667	.1826599	1.10	0.272	-.1583199	.5606533
atleast1_stemeco	.5242819	.3748293	1.40	0.163	-.2134067	1.261971
av_numindustries_exp	.0921408	.038679	2.38	0.018	.016018	.1682637
intern_netw	.2748205	.0666193	4.13	0.000	.1437093	.4059316
av_aclvlyrs_right	.1046509	.0583881	1.79	0.074	-.0102607	.2195625
ecomgt_crs	.1257498	.1646574	0.76	0.446	-.1983068	.4498064
av_numestabl	.2032807	.0805055	2.53	0.012	.0448406	.3617208
exp_bp	.0979209	.1492615	0.66	0.512	-.1958356	.3916774
_cons	.791217	.1542594	5.13	0.000	.4876244	1.09481

Figure 40: model 1.a – scientificity

Linear regression

Number of obs	305
F(10, 294)	7.06
Prob > F	0.0000
R-squared	0.1739
Root MSE	.77945

av_effectuat	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
fem_oneplus	-.0331892	.1052257	-0.32	0.753	-.2402803	.173902
maj_currstem	.01153	.1344604	0.09	0.932	-.253097	.2761569
maj_curreco	.0250211	.1331421	0.19	0.851	-.2370114	.2870535
atleast1_stemeco	.4098615	.2243629	1.83	0.069	-.0316994	.8514224
av_numindustries_exp	.0937452	.0259317	3.62	0.000	.0427098	.1447806
intern_netw	.2274303	.0500999	4.54	0.000	.1288303	.3260303
av_aclvlyrs_right	.05836	.0463086	1.26	0.209	-.0327784	.1494984
ecomgt_crs	.0144287	.1184408	0.12	0.903	-.2186705	.2475278
av_numestabl	.039839	.0641095	0.62	0.535	-.0863328	.1660107
exp_bp	.2385375	.1163337	2.05	0.041	.0095852	.4674898
_cons	1.498848	.1376093	10.89	0.000	1.228024	1.769672

Figure 41: model 1.a – effectuation

Now please look at Figures 40 and 41, where model 1.a is displayed: despite the low adjustment goodness measures (R-squared <0.2) due to the small specification size, this is the only model including the *atleast1_stemeco.* This variable results to be relevant as recording a positive correlation with the effectuative approach ($p<0.1$), whereas such positive influence suffers mitigation if related to scientificity ($0.1<p<0.15$). Thus the contemporaneous presences of at least 1 STEM student and at least 1 economics student positively affect the natural levels of both effectuation and scientificity, with the effect more pronounced in the first case. Yet, the variable *av_aclvlyrs_right* (i.e. average amount of years invested in university studies after the codification from academic level to numbers of years) shows enough low p-value ($0.05<p<0.1$) and positively affects the team scientificity; such is absolutely in line with the expectations, since the academic structured insights surely influence the students' mindset and decisional approach, so bringing a more rigid and scientific way to view the market and test hypotheses just like a scientist.

Looking at the proxies about individual experience, both the average number of ventures previously established (*av_numestabl*) and prior experience in business plan writing (*exp_bp*) registered statistical significance ($p<0.05$). The first one has positive correlation with the scientificity degree while the second positively affects the innate effectuative approach. So it looks like the number of firms already founded improves the ability in recognizing the market signals and understanding hot to meet the real needs, while the business planning experience suggests for higher seniority and empirical heritage and so a better orientation towards effectuative paradigm, which is indeed based more on features deriving from empirical insight rather than academic education. Finally the artificial variable named Internal Network (*intern_netw*), that measures the extent to which the startup team had previous ties in terms of work or university or other collaborations (its domain goes from zero up to 3), is strongly correlated with the dependent variables in every regression model here considered.

In particular, in 1.a specification it positively affects both scientificity and effectuation with the minimum p-value ($p<0.01$). That means the links among team members existing before the startup creation influence positively their decision-making activity; perhaps it comes from the fact that such characteristic helps the relationship conflict management, which is (along with the task conflict) the main issue brought by heterogenous composition in entrepreneurial teams. Indeed the diversity, according to what suggested by literature, improves performances through task conflict but negatively influences the group dynamics because of relationships conflict. Thus, high value in internal network predicts better capabilities of mitigating such conflict, so as to foster the team coordination during the feedback exchange phases (that is, a core activity in the scientific approach) while orchestrating the efforts assigned to flexibility, network and execution in effectuative decision-making.

Instead the model 1.b presents good values of explained variance (R-squared ≥ 0.3) despite the moderate amount of

variables considered. View in Figures 42 and 43, or alternatively in Appendix C, how the boolean referred to team majority attending economic university course (*maj_curreco*) is positively correlated with the scientificity, but not even with the effectuative aptitude. The statistical significance is low ($p<0.1$) but the effect was as expected: economics students are familiar with entrepreneurial business and with the technical tools usually used, and in addition they are more willing and accustomed to deal with market requirements and customer analysis, so that a major level of scientificity (meant as continuous feedback exchange between firm and market side) could be predicted.

After, also the average number (per team) of different industries in which the team members cultivated prior experience (*av_numindustries_exp*) results like one influencing factor. The coefficient is positive and highly significant ($p<0.01$) when the variable of interest is both scientificity and when effectuation. This proves again how the experience is important, but specifically this time in terms of heterogenous prior experiences: the more entrepreneur has worked in diverse sectors the more he will be able to follow a structured path (scientificity) or adapt his own strategies to the scope (effectuation). Yet, now looking at model 2.a (Figures 44 and 45) we can notice that startups declaring of offering an item that is product and service at the same time (*bothcomb_offer*) are prone to register higher scores both in scientific and effectuative approach, if compared to the ones focused on products (*prod_offer* is the omitted boolean variable). The model 2.a is interesting because of the significance registered by the academic level when treated as boolean rather than cardinal variable. The observed effect is ambiguous: both the boolean dimensions indicating whether the team majority holds a Master (*master-maj*) or a doctorate (*phd_maj*) title registered negative correlation with the sole effectuation (low significance, $p<0.1$); meanwhile the boolean used when the team majority currently attends M.Sc. course during IVL program (*msc_ing_maj*) is strongly ($p<0.01$) and positively correlated with both the dependent variables. The misalignment is surely due to the low numerousness of participants currently unrolled in university courses and, in particular, the records of the variable msc_ing_maj include just 6 people. By the way, by a theoretical standpoint the Master of Science level is high enough to guarantee good scientific skills (i.e. scientificity) while providing the right amount of experience needed to set his own strategies based on more empirical intuitions such as network, control, execution and flexibility (effectuation); on the other hand, a too high academic level (Master post-lauream and PhD) maybe could negatively influence the natural effectuative approach which puts roots on flexibility, execution and practical experience, namely features being often stiffened and obstructed by extremely high levels of standard academic education.

In conclusion, please view the model 3.b in Figures 46 and 47: as disclosed in model 5.b, the average level of Performance Avoid Orientation per startup (*av_pao*) is the main driver underlying to the variable *av_perforient,* indeed we can observe enough strong ($p<0.05$) negative correlation with the dependent variables;

so a negative psychological aptitude appears to negatively affects the decisional processes, and such evidence is absolutely in line with what expected ex-ante. The last point touches the heterogeneity dimension: the seniority Blau's index (*bu_age*) is positively related with both scientificity and effectuation natural levels, even if with superior intensity in the first case. Such last outcome is consistent according to the presented literature: differences in empirical experience and age bring diverse viewpoints and interpretation levels, other than the possibility of mixing more solid academic insights with previous practical experiences at work. The exact balance makes possible to apply rigid insight to the testing phase in order to corroborate (or not) hypotheses in a scientific way, as well as to merge the skills born from experience (control, execution, flexibility, network) with the solid market knowledge and business passion coming from academic environment. Of course, in the effectuation paradigm such diversity effect is mitigated as the experience has predominant weight, in other words the absolute seniority level is more relevant than the diversity property.

Linear regression

Number of obs	=	305				
F(11, 276)	=	.				
Prob > F	=	.				
R-squared	=	0.2990				
Root MSE	=	.97758				

av_scient	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
fem_oneplus	-.0191933	.1404056	-0.14	0.891	-.2955951	.2572086
maj_currstem	.1879371	.1602343	1.17	0.242	-.1274997	.5033738
maj_curreco	.3316374	.1855736	1.79	0.075	-.0336821	.6969569
av_numindustries_exp	.0972494	.0367441	2.65	0.009	.0249151	.1695837
intern_netw	.1324073	.0751778	1.76	0.079	-.0155873	.280402
av_aclvlyrs_right	.0909249	.0605806	1.50	0.135	-.0283339	.2101836
ecomgt_crs	.151932	.1580365	0.96	0.337	-.1591781	.4630421
av_numestabl	.1463348	.0805225	1.82	0.070	-.0121815	.3048511
exp_bp	.0050999	.1368163	0.04	0.970	-.2642361	.2744359
av_weekly_hrsxmember	.0155068	.0048967	3.17	0.002	.0058672	.0251464
su_numer	.190624	.0572552	3.33	0.001	.0779117	.3033363
suind_agric	2.38e-17	2.67e-16	0.09	0.929	-5.03e-16	5.50e-16
suind_commun	-2.48e-16	2.01e-16	-1.23	0.219	-6.45e-16	1.48e-16
suind_animcare	1.12e-16	3.36e-16	0.33	0.738	-5.49e-16	7.74e-16
suind_publishing	1.27e-15	1.90e-16	6.66	0.000	8.94e-16	1.64e-15
suind_electro	-2.66e-16	3.74e-16	-0.71	0.477	-1.00e-15	4.70e-16
suind_energ	-1.29e-15	4.07e-16	-3.16	0.002	-2.09e-15	-4.84e-16
suind_finance	-1.87e-16	2.64e-16	-0.71	0.479	-7.07e-16	3.32e-16
suind_food	-1.44e-16	2.43e-16	-0.59	0.555	-6.22e-16	3.35e-16
suind_educ	5.30e-16	2.82e-16	1.88	0.061	-2.41e-17	1.08e-15
suind_hardw	5.26e-16	2.02e-16	2.60	0.010	1.28e-16	9.24e-16
suind_entert	8.51e-17	3.62e-16	0.23	0.814	-6.28e-16	7.98e-16
suind_fash	-1.73e-16	2.29e-16	-0.76	0.450	-6.24e-16	2.78e-16
suind_health	-1.73e-17	1.97e-16	-0.09	0.930	-4.06e-16	3.71e-16
suind_induserv	-3.69e-16	2.21e-16	-1.67	0.096	-8.05e-16	6.64e-17
suind_homeserv	2.60e-16	5.00e-16	0.52	0.604	-7.25e-16	1.24e-15
suind_sw	1.36e-16	2.47e-16	0.55	0.584	-3.51e-16	6.22e-16
suind_transplog	-1.48e-16	3.96e-16	-0.37	0.709	-9.28e-16	6.33e-16
_cons	.3263589	.1973981	1.65	0.099	-.0622382	.714956

Figure 42: model 1.b – scientificity

Linear regression

Number of obs	=	305				
F(11, 276)	=	.				
Prob > F	=	.				
R-squared	=	0.3523				
Root MSE	=	.71235				

av_effectuat	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
fem_oneplus	-.1102574	.095549	-1.15	0.250	-.2983549	.0778401
maj_currstem	.0944473	.1168457	0.81	0.420	-.1355747	.3244693
maj_curreco	.1118786	.1363506	0.82	0.413	-.1565406	.3802978
av_numindustries_exp	.1021422	.0276463	3.69	0.000	.0477177	.1565667
intern_netw	.10008	.0497465	2.01	0.045	.0021492	.1980109
av_aclvlyrs_right	.0546492	.046399	1.18	0.240	-.0366917	.1459901
ecomgt_crs	.0471564	.115542	0.41	0.683	-.1802991	.2746119
av_numestabl	-.0399278	.0616729	-0.65	0.518	-.1613367	.0814812
exp_bp	.1703331	.1045452	1.63	0.104	-.0354742	.3761403
av_weekly_hrsxmember	.014097	.0032392	4.35	0.000	.0077204	.0204737
su_numer	.1875664	.0385709	4.86	0.000	.1116359	.263497
suind_agric	-1.51e-16	2.86e-16	-0.53	0.598	-7.14e-16	4.12e-16
suind_commun	-7.19e-17	1.27e-16	-0.57	0.572	-3.22e-16	1.78e-16
suind_animcare	-7.28e-16	1.69e-16	-4.31	0.000	-1.06e-15	-3.95e-16
suind_publishing	3.69e-16	1.40e-16	2.63	0.009	9.33e-17	6.45e-16
suind_electro	-5.28e-16	3.16e-16	-1.67	0.095	-1.15e-15	9.34e-17
suind_energ	-3.86e-16	3.49e-16	-1.10	0.270	-1.07e-15	3.02e-16
suind_finance	-6.81e-17	2.10e-16	-0.32	0.746	-4.82e-16	3.46e-16
suind_food	-1.77e-16	1.27e-16	-1.40	0.164	-4.27e-16	7.28e-17
suind_educ	2.48e-16	2.44e-16	1.01	0.311	-2.33e-16	7.28e-16
suind_hardw	5.16e-16	1.48e-16	3.49	0.001	2.25e-16	8.07e-16
suind_entert	4.26e-18	3.23e-16	0.01	0.989	-6.31e-16	6.40e-16
suind_fash	-7.96e-17	1.91e-16	-0.42	0.678	-4.56e-16	2.97e-16
suind_health	4.17e-17	1.47e-16	0.28	0.777	-2.48e-16	3.31e-16
suind_induserv	2.26e-16	3.14e-16	0.72	0.473	-3.93e-16	8.44e-16
suind_homeserv	-1.31e-16	2.82e-16	-0.47	0.641	-6.86e-16	4.23e-16
suind_sw	-3.25e-16	1.77e-16	-1.83	0.068	-6.74e-16	2.41e-17
suind_transplog	-1.31e-16	2.23e-16	-0.59	0.558	-5.71e-16	3.09e-16
_cons	1.080084	.1604068	6.73	0.000	.7643074	1.39586

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Figure 43: model 1.b – effectuation

Linear regression

Number of obs	305
F(17, 287)	5.82
Prob > F	0.0000
R-squared	0.2067
Root MSE	1.0198

av_scient	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
serv_offer	.4577178	.1292091	3.54	0.000	.2034001	.7120356
bothcomb_offer	.556404	.3025885	1.84	0.067	-.03917	1.151978
fem_oneplus	.086593	.1404129	0.62	0.538	-.1897766	.3629626
av_numindustries_exp	.0965263	.0374632	2.58	0.010	.0227888	.1702638
intern_netw	.2632471	.0653319	4.03	0.000	.1346567	.3918375
av_aclvlyrs_right	.1889809	.2237008	0.84	0.399	-.2513213	.629283
ecomgt_crs	.1351769	.1572866	0.86	0.391	-.1744046	.4447585
av_numestabl	.1572166	.0818149	1.92	0.056	-.0038166	.3182499
exp_bp	.1022089	.1448334	0.71	0.481	-.1828616	.3872794
bsc_maj	.0842146	.2194731	0.38	0.701	-.3477664	.5161955
msc_maj	-.2171524	.2346188	-0.93	0.355	-.6789441	.2446393
master_maj	-.1621489	.2253923	-0.72	0.472	-.6057804	.2814827
nothing_maj	.1550625	.5047863	0.31	0.759	-.8384903	1.148615
phd_maj	.3456292	.5048726	0.68	0.494	-.6480935	1.339352
bsc_ing_maj	.1666411	.3463389	0.48	0.631	-.5150453	.8483275
msc_ing_maj	1.523392	.4635407	3.29	0.001	.6110217	2.435763
master_ing_maj	-.3424846	.416117	-0.82	0.411	-1.161513	.4765435
postlaur_ing_maj	0	(omitted)				
_cons	.3354792	.5241609	0.64	0.523	-.6962078	1.367166

Figure 44: model 2.a – scientificity

Linear regression

Number of obs	305
F(17, 287)	5.77
Prob > F	0.0000
R-squared	0.2112
Root MSE	.77091

av_effectuat	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
serv_offer	.1396804	.1013526	1.38	0.169	-.0598082	.339169
bothcomb_offer	.4229173	.1831838	2.31	0.022	.0623632	.7834714
fem_oneplus	-.0049359	.1010504	-0.05	0.961	-.2038298	.1939581
av_numindustries_exp	.0947522	.0277521	3.41	0.001	.0401289	.1493756
intern_netw	.2395832	.0489322	4.90	0.000	.1432716	.3358947
av_aclvlyrs_right	.1898482	.1343483	1.41	0.159	-.0745848	.4542812
ecomgt_crs	-.015286	.1214693	-0.13	0.900	-.2543697	.2237976
av_numestabl	.0208347	.0637603	0.33	0.744	-.1046624	.1463318
exp_bp	.2273383	.1143228	1.99	0.048	.0023208	.4523557
bsc_maj	-.1022261	.1448319	-0.71	0.481	-.3872935	.1828413
msc_maj	-.1547344	.1791594	-0.86	0.388	-.5073674	.1978986
master_maj	-.3166325	.1773376	-1.79	0.075	-.6656798	.0324148
nothing_maj	.1008518	.2941464	0.34	0.732	-.478106	.6798097
phd_maj	-.711092	.3411911	-2.08	0.038	-1.382646	-.0395377
bsc_ing_maj	-.0266309	.2094147	-0.13	0.899	-.4388143	.3855525
msc_ing_maj	1.014123	.2780632	3.65	0.000	.466821	1.561425
master_ing_maj	-.3647433	.3602164	-1.01	0.312	-1.073744	.3442578
postlaur_ing_maj	0	(omitted)				
_cons	1.294985	.3144412	4.12	0.000	.6760817	1.913888

Figure 45: model 2.a – effectuation

Linear regression — Number of obs = 298; F(20, 260) = .; Prob > F = .; R-squared = 0.3122; Root MSE = .98544

av_scient	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
bu_gender	-.5488093	.4407479	-1.25	0.214	-1.416699	.3190805
bu_age	1.420344	.5980672	2.37	0.018	.2426724	2.598017
bu_region	.4840808	.5936114	0.82	0.416	-.6848173	1.652979
bu_maxaclvl	-.0131118	.397895	-0.03	0.974	-.7966189	.7703952
bu_othcom	-.2332386	.4880081	-0.48	0.633	-1.19419	.7277128
bu_curstude	.1524453	.6871848	0.22	0.825	-1.200711	1.505601
bu_expbp	-.0250264	.4363581	-0.06	0.954	-.8842721	.8342194
bu_alrestabl	.1749959	.5249249	0.33	0.739	-.8586495	1.208641
suind_agric	4.83e-17	2.57e-16	0.19	0.851	-4.58e-16	5.55e-16
suind_commun	1.11e-16	2.21e-16	0.50	0.616	-3.24e-16	5.46e-16
suind_animcare	-4.84e-16	2.57e-16	-1.88	0.061	-9.90e-16	2.20e-17
suind_publishing	1.44e-15	2.66e-16	5.42	0.000	9.17e-16	1.96e-15
suind_electro	-1.73e-16	3.57e-16	-0.48	0.630	-8.76e-16	5.31e-16
suind_energ	-7.83e-16	2.54e-16	-3.09	0.002	-1.28e-15	-2.83e-16
suind_finance	-2.60e-17	2.36e-16	-0.11	0.913	-4.91e-16	4.39e-16
suind_food	-1.60e-16	2.45e-16	-0.65	0.515	-6.41e-16	3.22e-16
suind_educ	5.18e-16	3.24e-16	1.60	0.111	-1.20e-16	1.15e-15
suind_hardw	5.70e-16	3.20e-16	1.78	0.076	-6.02e-17	1.20e-15
suind_entert	1.40e-16	3.67e-16	0.38	0.704	-5.83e-16	8.62e-16
suind_fash	-1.07e-16	2.38e-16	-0.45	0.655	-5.75e-16	3.62e-16
suind_health	-2.68e-17	1.91e-16	-0.14	0.889	-4.04e-16	3.50e-16
suind_induserv	-5.16e-16	2.01e-16	-2.57	0.011	-9.11e-16	-1.21e-16
suind_homeserv	4.39e-16	4.93e-16	0.89	0.374	-5.31e-16	1.41e-15
suind_sw	7.22e-17	2.50e-16	0.29	0.773	-4.20e-16	5.64e-16
suind_transplog	-4.26e-16	3.65e-16	-1.17	0.243	-1.14e-15	2.91e-16
av_weekly_hrsxmember	.0142258	.0050898	2.79	0.006	.0042034	.0242482
su_numer	.1717969	.0637484	2.69	0.007	.0462681	.2973257
av_workexpyrs	.002909	.0083285	0.35	0.727	-.0134909	.019309
exp_bp	.0764741	.1366179	0.56	0.576	-.1925443	.3454925
av_horiz2	.0543937	.0386798	1.41	0.161	-.0217718	.1305592
av_selfesteem	.0206252	.0585736	0.35	0.725	-.0947138	.1359641
av_pgo	-.101071	.0487483	-2.07	0.039	-.1970627	-.0050793
av_shapeident	.0601427	.0512896	1.17	0.242	-.0408532	.1611387
av_teambuild	-.0216161	.0286355	-0.75	0.451	-.078003	.0347709
intern_netw	.1198458	.083354	1.44	0.152	-.0442891	.2839806
av_focusident	.0435786	.0793321	0.55	0.583	-.1126367	.1997939
av_supident	-.0275264	.0825744	-0.33	0.739	-.1901261	.1350734
_cons	.4799104	.3661192	1.31	0.191	-.241026	1.200847

Figure 46: model 3.b – scient.

Linear regression — Number of obs = 298; F(20, 260) = .; Prob > F = .; R-squared = 0.3609; Root MSE = .71813

av_effectuat	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
bu_gender	-.1570575	.2830799	-0.55	0.579	-.7144786	.4003636
bu_age	.6870196	.3594877	1.91	0.057	-.0208583	1.394898
bu_region	.1134681	.4148222	0.27	0.785	-.7033708	.9303069
bu_maxaclvl	-.0975631	.2988161	-0.33	0.744	-.6859709	.4908447
bu_othcom	-.2994081	.3230398	-0.93	0.355	-.9355155	.3366993
bu_curstude	.5084535	.3921581	1.30	0.196	-.2637568	1.280664
bu_expbp	.1161127	.2793706	0.42	0.678	-.4340043	.6662298
bu_alrestabl	-.1071954	.3480499	-0.31	0.758	-.792551	.5781601
suind_agric	-1.62e-16	2.89e-16	-0.56	0.576	-7.31e-16	4.07e-16
suind_commun	1.73e-16	1.52e-16	1.14	0.256	-1.27e-16	4.73e-16
suind_animcare	-1.03e-15	2.77e-16	-3.72	0.000	-1.58e-15	-4.85e-16
suind_publishing	4.20e-16	2.16e-16	1.95	0.053	-5.03e-18	8.46e-16
suind_electro	-4.96e-16	3.39e-16	-1.46	0.145	-1.16e-15	1.72e-16
suind_energ	1.55e-16	1.53e-16	1.02	0.311	-1.46e-16	4.56e-16
suind_finance	-3.47e-17	2.27e-16	-0.15	0.879	-4.82e-16	4.13e-16
suind_food	-2.08e-16	1.40e-16	-1.49	0.139	-4.83e-16	6.76e-17
suind_educ	1.15e-16	2.47e-16	0.47	0.641	-3.71e-16	6.02e-16
suind_hardw	6.58e-16	1.91e-16	3.45	0.001	2.82e-16	1.03e-15
suind_entert	-1.88e-17	3.05e-16	-0.06	0.951	-6.19e-16	5.82e-16
suind_fash	-4.20e-17	1.93e-16	-0.22	0.828	-4.22e-16	3.38e-16
suind_health	3.42e-17	1.43e-16	0.24	0.811	-2.47e-16	3.16e-16
suind_induserv	4.14e-17	3.28e-16	0.13	0.900	-6.05e-16	6.88e-16
suind_homeserv	-5.78e-17	2.63e-16	-0.22	0.826	-5.76e-16	4.60e-16
suind_sw	-3.34e-16	1.71e-16	-1.96	0.052	-6.71e-16	2.35e-18
suind_transplog	-3.94e-16	2.31e-16	-1.70	0.090	-8.49e-16	6.13e-17
av_weekly_hrsxmember	.0129446	.0031415	4.12	0.000	.0067585	.0191307
su_numer	.1597161	.0371703	4.30	0.000	.0865229	.2329092
av_workexpyrs	.0011934	.0063166	0.19	0.850	-.0112448	.0136316
exp_bp	.169543	.1075451	1.58	0.116	-.0422273	.3813132
av_horiz2	.0261922	.0300235	0.87	0.384	-.0329279	.0853124
av_selfesteem	.0445588	.0435955	1.02	0.308	-.0412863	.130404
av_pgo	-.1012217	.0429352	-2.36	0.019	-.1857667	-.0166767
av_shapeident	.0323417	.0410902	0.79	0.432	-.0485702	.1132536
av_teambuild	-.0078143	.0255836	-0.31	0.760	-.0581917	.0425632
intern_netw	.1013412	.052897	1.92	0.056	-.0028199	.2055024
av_focusident	.0306908	.0518111	0.59	0.554	-.0713321	.1327137
av_supident	.030419	.0575116	0.53	0.597	-.0828289	.1436668
_cons	.9589339	.302545	3.17	0.002	.3631835	1.554684

Figure 47: model 3.b – effectuat.

4.3 Robustness check

A further control has been done by excluding the startups which declared a different number of team members (i.e. 111) if compared to the ones who actually responded the interviews/surveys. This has been done in order to obtain a new less dirty dataset with more reliable data, since at the origin some observed effects could be biased and distorted given the information loss: i.e., for a given record a high positive correlation has been individuated between age heterogeneity and natural scientific level, but in fact the age heterogeneity (*bu_age*) bases on fake data, so that real composition in seniority could even deeply differ if compared to what tracked into the database. The findings coming from such change are completely in line with the original models, except for two variables: heterogeneities in gender (*bu_gender*) and in business plan writing experience (*bu_expbp*). The adjustment goodness measures (Figures 48 and 49) improve on overage thanks to the superior data quality: R-squared becomes 0.5737 (in place of 0.4296) and 0.5427 (in place of 0.5433) respectively when dependent variable is the natural level of scientificity and effectuation. In the model 5.b.RC it is relevant to note how a number of new dimensions become correlated with the scientificity variable: previous experience in attended entrepreneurship courses (*entrep_crs*), team average degree of team building orientation (*av_teambuild*), other than the already cited heterogeneities in gender and in experience as business planner. The *entrep_crs* indicates the percentage of members who already attended entrepreneurship courses (before IVL) for each startup, and here seems to be positively linked to high levels of scientificity: this is an expected result, given that several courses focus on structured decisional methods and well-defined tools. The team building instead measures the inclination of each individual towards the others, in terms of searching for the best means to communicate and collaborate, as well as avoiding conflicts and declaring mental opening during the comparison with external environment. It negatively related to scientificity, maybe deriving from the poorly competitive nature of the members, who lack of great stimulus and therefore are not able to focus on the objective by setting structured paths and strategies. By the way please consider that its p-value is very high (more than 9%). Finally, the Blau's indicators about gender and business plan experience show negative correlation with the natural scientific approach, looking like such differences lead worse relationship conflict management which outperforms the benefit coming from a better task conflict management – even though we have to underline that also in this case the p-values are high, respectively equal to 8% (gender) and 7.3% (business plan writing). The news arising from the model 5.b.RC do not keep the same within the specification where effectuation is dependent variable: this is to corroborate that heterogeneity has largely more influence on the structured dynamics of feedback exchange which characterize the scientific paradigm, while are not a central driver for the natural effectuation level, which pays more attention to enough abstract abilities such as network, control, execution and flexibility, less suffering the effect brought by task conflict and relationship conflict management.

Linear regression

Number of obs	191
F(42, 129)	.
Prob > F	.
R-squared	0.5737
Root MSE	.86864

av_scient	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
suind_agric	5.52e-16	2.67e-16	2.06	0.041	2.25e-17	1.08e-15
suind_commun	-4.97e-16	3.48e-16	-1.43	0.155	-1.18e-15	1.91e-16
suind_animcare	-6.00e-16	3.17e-16	-1.89	0.061	-1.23e-15	2.77e-17
suind_publishing	1.24e-15	2.73e-16	4.52	0.000	6.95e-16	1.78e-15
suind_electro	2.03e-17	4.57e-16	0.04	0.965	-8.84e-16	9.24e-16
suind_energ	-2.07e-15	4.81e-16	-4.31	0.000	-3.02e-15	-1.12e-15
suind_finance	8.36e-18	4.06e-16	0.02	0.984	-7.96e-16	8.13e-16
suind_food	6.16e-16	4.00e-16	1.54	0.126	-1.75e-16	1.41e-15
suind_educ	3.08e-16	3.29e-16	0.94	0.350	-3.42e-16	9.58e-16
suind_hardw	1.66e-15	5.71e-16	2.90	0.004	5.26e-16	2.78e-15
suind_entert	3.27e-17	5.20e-16	0.06	0.950	-9.97e-16	1.06e-15
suind_fash	-1.00e-16	2.52e-16	-0.40	0.691	-6.00e-16	3.99e-16
suind_health	-5.09e-17	2.75e-16	-0.19	0.853	-5.95e-16	4.93e-16
suind_induserv	-7.28e-16	3.02e-16	-2.41	0.017	-1.33e-15	-1.30e-16
suind_homeserv	5.92e-16	5.35e-16	1.11	0.271	-4.67e-16	1.65e-15
suind_sw	2.57e-16	2.95e-16	0.87	0.384	-3.26e-16	8.40e-16
suind_transplog	-4.64e-16	2.90e-16	-1.60	0.113	-1.04e-15	1.11e-16
center	1.12e-16	2.31e-16	0.49	0.628	-3.44e-16	5.68e-16
south	-2.73e-16	1.64e-16	-1.66	0.099	-5.99e-16	5.20e-17
su_numer	.4137085	.1226525	3.37	0.001	.1710376	.6563794
av_weekly_hrsxmember	.008497	.0061771	1.38	0.171	-.0037245	.0207184
su_ph2	.9814083	.2503876	3.92	0.000	.4860102	1.476806
su_ph3	.9562127	.3816878	2.51	0.013	.201034	1.711391
su_ph4	.301196	.9444703	0.32	0.750	-1.567462	2.169854
su_ph5	-.2337361	.4297454	-0.54	0.587	-1.083998	.6165257
serv_offer	.4783064	.1641867	2.91	0.004	.1534591	.8031537
bothcomb_offer	.4072034	.4432242	0.92	0.360	-.4697265	1.284133
av_aclvlyrs_right	.2019029	.2974443	0.68	0.498	-.3865979	.7904037
av_numindustries_exp	.023005	.0516731	0.45	0.657	-.0792315	.1252415
alr_establ	-.020333	.338604	-0.06	0.952	-.6902692	.6496032
av_numestabl	.0507474	.1790086	0.28	0.777	-.3034255	.4049202
exp_bp	-.183793	.1806356	-1.02	0.311	-.5411851	.173599
ecomgt_crs	.1657461	.2242036	0.74	0.461	-.2778462	.6093383
entrep_crs	.3570682	.2040435	1.75	0.083	-.0466369	.7607733
av_horiz2	.0487448	.0483366	1.01	0.315	-.0468903	.1443798
intern_netw	.1822496	.1078275	1.69	0.093	-.0310897	.395589
diff_usab	-.045722	.1367975	-0.33	0.739	-.3163792	.2249352
av_rlvncoth	.0103708	.0203668	0.51	0.611	-.0299254	.050667
av_pgo	.0723828	.1104582	0.66	0.513	-.1461614	.2909271
av_perforient	-.0730949	.0669546	-1.09	0.277	-.2055662	.0593765
av_solveident	-.0117579	.0763203	-0.15	0.878	-.1627595	.1392437
av_shapeident	.0527411	.074933	0.70	0.483	-.0955157	.2009979
av_focusident	.0422515	.0719391	0.59	0.558	-.1000818	.1845849
av_supident	-.0367657	.0808222	-0.45	0.650	-.1966744	.123143
av_teambuild	-.0644443	.0379104	-1.70	0.092	-.1394508	.0105623
bu_gender	-1.010176	.5722909	-1.77	0.080	-2.142467	.1221159
bu_age	1.534037	.7963632	1.93	0.056	-.0415872	3.109661
bu_region	-.3235068	.7795307	-0.42	0.679	-1.865827	1.218814
bu_maxaclvl	-1.001429	.6496801	-1.54	0.126	-2.286837	.2839791
bu_othcom	.4197152	.6365239	0.66	0.511	-.839663	1.679093
bu_curstude	.2334671	.7677285	0.30	0.762	-1.285503	1.752437
bu_expbp	-1.112322	.6145352	-1.81	0.073	-2.328195	.1035506
bu_alrestabl	.3597434	.8016875	0.45	0.654	-1.226415	1.945902
bsc_maj	-.1372515	.274952	-0.50	0.619	-.6812507	.4067477
msc_maj	-.2241985	.3807546	-0.59	0.557	-.9775308	.5291338
master_maj	.2122674	.425673	0.50	0.619	-.6299371	1.054472
nothing_maj	.5083051	.5635349	0.90	0.369	-.6066625	1.623273
phd_maj	.0988492	1.070858	0.09	0.927	-2.01987	2.217569
bsc_ing_maj	.2129902	.3804512	0.56	0.577	-.5397418	.9657222
msc_ing_maj	2.389473	.6189426	3.86	0.000	1.16488	3.614066
master_ing_maj	-.5791949	.5922043	-0.98	0.330	-1.750886	.5924958
postlaur_ing_maj	0	(omitted)				
_cons	-.2671007	.7542787	-0.35	0.724	-1.75946	1.225258

Figure 48: model 5.b.RC – scientificity

Linear regression

Number of obs	191
F(42, 129)	.
Prob > F	.
R-squared	0.5427
Root MSE	.68707

av_effectuat	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
suind_agric	3.08e-16	3.80e-16	0.81	0.419	-4.45e-16	1.06e-15
suind_commun	-2.75e-16	2.20e-16	-1.25	0.214	-7.09e-16	1.60e-16
suind_animcare	-6.68e-16	2.96e-16	-2.26	0.026	-1.25e-15	-8.25e-17
suind_publishing	1.56e-16	2.57e-16	0.61	0.543	-3.51e-16	6.64e-16
suind_electro	-3.13e-16	4.93e-16	-0.64	0.526	-1.29e-15	6.63e-16
suind_energ	-3.95e-16	2.98e-16	-1.33	0.187	-9.84e-16	1.94e-16
suind_finance	2.70e-18	2.75e-16	0.01	0.992	-5.42e-16	5.47e-16
suind_food	-8.49e-17	2.45e-16	-0.35	0.729	-5.69e-16	3.99e-16
suind_educ	-2.25e-16	1.96e-16	-1.15	0.252	-6.12e-16	1.62e-16
suind_hardw	7.02e-16	3.89e-16	1.80	0.073	-6.76e-17	1.47e-15
suind_entert	6.17e-16	3.40e-16	1.81	0.072	-5.58e-17	1.29e-15
suind_fash	-1.15e-16	2.67e-16	-0.43	0.667	-6.45e-16	4.14e-16
suind_health	6.55e-17	2.14e-16	0.31	0.760	-3.58e-16	4.89e-16
suind_induserv	2.39e-16	3.30e-16	0.73	0.470	-4.13e-16	8.91e-16
suind_homeserv	3.15e-16	4.11e-16	0.77	0.445	-4.98e-16	1.13e-15
suind_sw	-5.76e-16	2.58e-16	-2.23	0.027	-1.09e-15	-6.60e-17
suind_transplog	-1.96e-16	3.21e-16	-0.61	0.544	-8.32e-16	4.40e-16
center	-1.55e-16	1.54e-16	-1.00	0.318	-4.60e-16	1.50e-16
south	-2.41e-16	1.37e-16	-1.76	0.080	-5.12e-16	2.93e-17
su_numer	.1626557	.0771136	2.11	0.037	.0100847	.3152268
av_weekly_hrsxmember	.0105903	.0040596	2.61	0.010	.0025583	.0186223
su_ph2	.7434093	.1485553	5.00	0.000	.4494891	1.03733
su_ph3	.2266015	.256493	0.88	0.379	-.2808762	.7340792
su_ph4	.5807498	.6042856	0.96	0.338	-.6148442	1.776344
su_ph5	.3977273	.3004663	1.32	0.188	-.1967527	.9922073
serv_offer	.149583	.1524245	0.98	0.328	-.1519926	.4511587
bothcomb_offer	.6531102	.2845177	2.30	0.023	.0901849	1.216036
av_aclvlyrs_right	.1623671	.205581	0.79	0.431	-.24438	.5691141
av_numindustries_exp	.0418674	.0389921	1.07	0.285	-.0352795	.1190143
alr_establ	.581276	.2509858	2.32	0.022	.0846943	1.077858
av_numestabl	-.2756356	.117882	-2.34	0.021	-.5088681	-.042403
exp_bp	.225509	.1584751	1.42	0.157	-.0880379	.539056
ecomgt_crs	.1407906	.1708629	0.82	0.411	-.1972657	.478847
entrep_crs	-.1843757	.1899018	-0.97	0.333	-.5601012	.1913497
av_horiz2	.0309786	.0413025	0.75	0.455	-.0507395	.1126967
intern_netw	.124917	.0982952	1.27	0.206	-.0695624	.3193964
diff_usab	-.1170473	.1233203	-0.95	0.344	-.3610396	.126945
av_rlvncoth	.0114406	.016005	0.71	0.476	-.0202258	.0431069
av_pgo	.0974339	.1115147	0.87	0.384	-.1232007	.3180685
av_perforient	-.084029	.0595675	-1.41	0.161	-.2018846	.0338267
av_solveident	.0123439	.0553957	0.22	0.824	-.0972577	.1219456
av_shapeident	.0105241	.0550423	0.19	0.849	-.0983785	.1194267
av_focusident	.0216599	.0736826	0.29	0.769	-.124123	.1674427
av_supident	.0040265	.0820435	0.05	0.961	-.1582985	.1663515
av_teambuild	-.0401921	.0325197	-1.24	0.219	-.1045331	.0241489
bu_gender	-.1974604	.4895415	-0.40	0.687	-1.16603	.7711096
bu_age	.7550792	.5058596	1.49	0.138	-.2457763	1.755935
bu_region	-.0583361	.6812139	-0.09	0.932	-1.406134	1.289462
bu_maxaclvl	-.2729654	.4893562	-0.56	0.578	-1.241169	.6952379
bu_othcom	-.0909258	.4538437	-0.20	0.842	-.9888667	.8070152
bu_curstude	.5562083	.479729	1.16	0.248	-.3929472	1.505364
bu_expbp	.5259144	.3900733	1.35	0.180	-.2458552	1.297684
bu_alrestabl	-.7223603	.5280066	-1.37	0.174	-1.767034	.3223137
bsc_maj	-.3051772	.2004554	-1.52	0.130	-.7017832	.0914288
msc_maj	-.0966752	.2962902	-0.33	0.745	-.6828927	.4895423
master_maj	-.1487034	.3045702	-0.49	0.626	-.751303	.4538962
nothing_maj	.091202	.3975059	0.23	0.819	-.6952732	.8776772
phd_maj	-.8612011	.6627445	-1.30	0.196	-2.172457	.4500551
bsc_ing_maj	-.0667725	.2430882	-0.27	0.784	-.5477284	.4141834
msc_ing_maj	1.022892	.4294667	2.38	0.019	.1731813	1.872602
master_ing_maj	-.9901726	.4970096	-1.99	0.048	-1.973518	-.0068269
postlaur_ing_maj	0	(omitted)				
_cons	1.057765	.4962011	2.13	0.035	.0760185	2.039511

Figure 49: model 5.b.RC – effectuation

4.4 Final conclusions

In this paragraph the resulting outcomes will be explicited in light of what studied in literature. Before passing to the final discussion, please note that there is a narrow set of variables strongly influencing the dependent variables, and above all the *av_numindustries_exp* and *intern_netw* showed to be statistically significant in every regression model, other than always record high degrees of significance. Taking into consideration, for instance, what happened in model 1.a, it is possible to proceed with a sensitivity analysis on the natural scientificity level by varying the values of the two just mentioned independent variables, while keeping the other regressors fixed to their domain's superior limit (and obviously the coefficients equal to what defined by regression model). In Figure 50 the analysis is shown, and above the table please note there is the functional form belonging to the considered linear regression. The average number (per startup) of diverse industries in which the members got experience changes in its own domain by varying the column, whereas the value of team internal network increases by going down along the first column. As expected, even though the number of regressors is quite great (10 + intercept), the dependent variable deeply modifies with variation of these two regressors, and the scientific approach innate intensity is highlighted with different purple shades by exploiting the conditional formatting.

Now we come to the research conclusions. To sum up, the answer to the first research question is that the aggregated Blau's index never registers statistical correlation, and such is due to the general low correlation between the sub-indicators separately considered and the dependent variables. Indeed only the age heterogeneity resulted to be positively and highly linked to the variables of interest. It suggests for a strong contribute brought by merging academic insight and practical experience in order to improve the build-measure-learn cycles (i.e. scientificity) and the capability of focusing on execution while keeping flexibility and attention on contact ties. However the *bu_age* has relevant statistical significance for both scientificity and effectuation just in two models, that is 3.a and 3.b; indeed more in general it showed to be more influencing on scientific approach rather than effectuative behavior. This is to confirm that the experience diversity factor is deeply crucial just for the scientific paradigm since it puts roots on the continuous feedback exchange and test comparison.

$$av\_scient = \beta_0 + \beta_1 * fem_{oneplus} + \beta_2 * maj_{currstem} + \beta_3 * maj_{curreco} + \beta_4 * atleast1_{stemeco} + \beta_5 * av\_numindustries\_exp + \beta_6 * intern_{netw} + \beta_7 * av\_aclvlyrs_{right} + \beta_8 * ecomgt_{crs} + \beta_9 * av_{numestabl} + \beta_{10} * exp\_bp$$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	3,0747	3,1668	3,2589	3,351	3,4431	3,5352	3,6273	3,7194	3,8115	3,9036	3,9957	4,0878	4,1799	4,272
1	3,3495	3,4416	3,5337	3,6258	3,7179	3,81	3,9021	3,9942	4,0863	4,1784	4,2705	4,3626	4,4547	4,5468
2	3,6243	3,7164	3,8085	3,9006	3,9927	4,0848	4,1769	4,269	4,3611	4,4532	4,5453	4,6374	4,7295	4,8216
3	3,8991	3,9912	4,0833	4,1754	4,2675	4,3596	4,4517	4,5438	4,6359	4,728	4,8201	4,9122	5,0043	5,0964

Figure 50: sensitivity analysis in model 1.a – scientificity is variable of interest

Such is a process fostered by a good task conflict management, meant as the concept introduced by Jehn et al. (1997, 1999) in opposition to the relationship conflict management. Right the latter point arises too from the evidence about control variable Internal Network: it is statistically significant in all the regression specifications, and with positive influence in every scenario. Perhaps this is evidence that preexisting ties among team members can positively affect the decision-making process through a better relationship conflict management, thus mitigating divergences deriving from heterogeneity. A separate mention deserve the Blau indicators about students' presence, gender and business plan experience. The students' presence appears as significant only in model 5.b and for sole effectuation, other than with the lowest significance level ($p<0.1$) – therefore it does not represent a strong evidence, also seen that diversity in commitment on study is someway a proxy of diversity in seniority, so that a similar outcome would be expected (instead of no relationship with the natural scientific aptitude). After, diversities in gender and experience in business plan are relevant only in models belonging to the robustness check; they however affect only the scientific approach and do it with too high levels of significance, respectively of 8% and 7.3% - such is a very weak evidence, and in addition 1) no other relevant outcomes have been emerged about gender boolean variables whereas 2) there is apparently no reason why the previous BP activity should be relevant for a dependent variable but not for another. The ambiguousness of some findings underlined the primary doubts claimed in the wide literature (Phillips & O'Reilly, 1998) produced on the argument, anyway the prominent relationship conflict management weight suggested by a number of different authors (Jehn et al. 1997; Klotz et al., 2014; Fitzgerald et al., 2017; Zhang, 2019) is here confirmed, thanks to what found on the internal network variable and its mitigating effects.

Coming to the second research question, investigating the influence of external networks represent an issue given the lack of such information into the database at time zero. In addition, the LinkedIn contacts counting already proposed in recent studies should be biased in this experiment seen the nature of participants, mostly young and with few professional experience, so that a series of control variables was proposed at the beginning of this thesis project. Among the various control variables just cited, the only ones which registered relevant correlation have been the students' presence Blau and the team numerousness. The first one is a dimension on which also the Geremias' (2020) studies put a focus, but in this thesis project has resulted as not relevant given that influenced the sole effectuation by registering also high p-value ($p<0.1$) – despite the poor correlation, in terms of external network its relevance can be explained by thinking that the presence of students and experienced people at the same time might guarantee access to heterogenous set of resources and information, otherwise not reachable from an unique group as remembered by Aldrich and Kim (2007). This is clearly expected to affect the natural effectuation level, since the network dimension is right one of its pillars. The startup team

numerosity is instead an evident proxy of how many external ties the team is potentially able to achieve: the more the team members are, the more they could merge their different contacts with the aim of creating a stable and loyal business network. The *su_numer* independent variable is positively related to both scientificity and effectuation in every regression model and always with extreme significance ($p<0.01$), except in specification 5.b (no relationship with scientificity degree) – that result is in line with its control functionality, since the capability of measuring the network extent was expected to be crucial more in effectuative than scientific approach, and this is what underlined by the exception model (5.b); anyway, please consider that this is only a starting point in order to set more in-depth analyses in the future, given the lack of useful information in the dataset at time zero. We must also consider that use of psychological traits as control variable has not been fruitful, since no particular relationship was found and this lack of evidences is in opposition with a huge number of papers in literature (Reagans et al., 2004; Arif T., 2015; Jurkevičienė et al., 2018).

Looking at the third research question, unfortunately no variable underlying to the psychological capital (Wang et al., 2019) resulted as influencing the decision-making process, except for the Performance Avoid Orientation: according to the dimensions defined in a narrow group of studies (e.g., St-Jean & Tremblay, 2020; Uy et al., 2017), the PAO variable in model 3.b negatively affects both scientificity and effectuation with enough good p-value ($p<0.05$), and that was a predictable effect given that toxic work aptitudes surely lead to worse performances in decisional processes too. Referring to what written in the recent study of Alessandri et al. (2018), the work engagement has been tracked through the control variable *av_weekly_hrsxmember* (average number of hours that each team member weekly invests on the startup) and resulted as statistically significant throughout all the regression models, with positive influence on both natural levels of scientific and effectuative approach. Fixed the dependence between hours of engagement and decision-making process, it remains quite hard to link such engagement measure with specific individual traits since they did not appear being significant in any specification. Additionally, as discussed by Amit (2001), also the prior experience in business plan writing demonstrated to be influencing: it has positive coefficient compared to the innate effectuative approach (models 1.a and 2.a, $p<0.05$), thus proving a real tie between the practical business plan experience and the capabilities needed in the effectuative framework. By the way, it is again not possible to link such variable to the individual psychological capital since no evidence emerged in that sense. In conclusion, no findings have arised about the psychological cluster, in opposition to what suggested by literature about traits such as risk appetite (Su-li & Ke-fan, 2011), self-esteem and openness toward novelty (Clark & Wiesenfeld, 2017), bias presence (York et al., 2014) and initial personal motivations (Shah & Tripsas, 2007-2012).

Instead, the fourth research question aimed to investigate whether secondary discriminants like kind of offering and industry can affect someway the innate

decision-making aptitudes. Indeed Schleimer and Shulman (2011) discovered positive differences in profitability coming from product nature compared to the service world, so that also differences in the used decisional processes were expected, maybe due to the physical nature of product vis-à-vis the more abstract service concept. In the experiment analyzed by this thesis work, the offerings appear being positively correlated with the sole scientific approach (and always with optimum values of statistical significance) when they are services. It can be due to the fact that the flexible nature of the services makes easier to create continuous feedback exchange with market and customers, so that phases of test and validation come to be facilitated thanks to the possibility of completing the entire process by only using online means, with consequent less time wasting and more efficient learning. Yet, Mitchell and Shepherd (2010) proved that decision-making tends to be excessively risky and inconsistent when acting in more dynamic industries: our results seem to partially corroborate their findings, because belonging to the software industry negatively related to the sole innate effectuation degree, and the registered p-value is robust ($p<0.01$) in the models explaining more variance (i.e. 5.a and 5.b), namely those recording the best R-squared values (whereas $p<0.1$ in models 1.b and 3.b). Please note that the software-sector boolean is the unique one having enough numerous records (around 9% of the whole sample) in that category, so that the results should be sufficiently reliable. A relationship would have been expected with the natural scientificity level rather than the effectuative approach, seen that excessively risky and inconsistent decisions can derive from errors in feedback interpretation and test phase; by the way, we must consider that the final outcome could be distorted by seniority effects, which can maybe introduce deviations in the evidences from software sector given its dynamic and young nature. Finally, Anna et al. (2000) suggested for including the gender feature as control to investigate potential internal differences into the industry effect. In particular, they proposed to understand whether the business owners in traditional-men (or symmetrically in traditional-women) industries show different decisional aptitudes if compared to non-traditional ones. Unfortunately, it has been not possible to scrutinize such point given the lack of arised evidences about gender differences within the treated experiment, both in terms of team composition and heterogeneity.

Now we come to the fifth research question: better understanding the ties between academic influence and decision-making process. Looking at the background type at level team (rather than leader), in model 1.b when the team majority currently attends economics courses then the scientificity degree is higher ($p<0.1$), while in model 1.a when the team includes at least one member studying STEM and at least one member studying economics subject then the effectuative aptitude is greater. Such difference born thanks to the academic influence is in line with what told in literature (Greenwald and Banaji, 1995; Miozzo and Di Vito, 2016; Toma, 2020). Furthermore, the after-codification average academic level per team (*av_aclvlyrs_right*) positively affects the scientific approach in model 1.a ($p<0.1$),

but please note that the three just cited variables registered poor levels of significance, that are always near to 10% in p-value. Excellent significance is instead guaranteed ($p<0.01$) by the boolean indicating when team majority is engaged with a M.Sc. while attending IVL program (*msc_ing_maj*): it is positively linked to both innate scientificity and effectuation in models 2.a, 2.b and 5.b – therefore an high academic level in progress can provide the needed technical insights to conduct appropriate test phases and use right data validation tools (scientific approach), along with offering the amount of experience necessary for balancing abilities of execution, network, control and flexibility. Yet, according to Chatterji et al. (2019), too high academic achievements make become resistant to the capabilities needed in the effectuation framework: this is what arised from who already obtained a Master post-lauream (*master_maj*) or PhD (*phd_maj*), since these two dimensions negatively related with effectuation into the model 2.a – even if we have to underline that the significance value is not widely robust ($0.05<p\text{-value}<0.1$) . The top university levels negatively influence the natural effectuative approach maybe because the latter puts roots on flexibility, execution, and practical experience, namely features being often stiffened and obstructed by extremely high levels of standard academic education.

The sixth research question aims to discover whether tie between prior experiences and decision-making quality exists (Gimeno et al., 1994; Tornikoski, 2007; Preisendorfer et al., 2012; Cassar, 2014). The accumulated experience is difficult to replicate and allows entrepreneurs to understand competitive structure and market strengths, quality standards and most profitable trends. It improves capability of performing more precise predictions, along with diminishing the usually observed effects of discouragement that emerge after the initial instants; thus, experience influences decision-making thanks to a better comprehension. The outcomes from STATA indicate that correlation exists and always presents positive verse. By using the team as reference, the average amount of different industries in which members have cultivated direct experience (*av_numindustries_exp*) is strongly linked to higher values of scientificity and effectuation into all the regression models analyzed. More in particular, even if the significance level is nearly always robust ($p<0.01$), the latter seems being slightly higher for effectuation in models 5.a, 5.b, 1.a and 2.b – such is consistent with what described in literature, namely the effectuative approach is someway strictly linked to the experience dimension so that the effect of this variable was expected to be more pronounced on effectuation, even if positive influence on scientificity is obviously due to the utility coming from heterogenous and relevant prior work experiences. That is an interesting point also in light of the studies of Fern et al. (2012): they observed how entrepreneurs tend to overly rely on their own historical industry experiences, but discovered those with more different experiences showed less pronounced bias. Yet, the fact of already having established some firms (*alr_establ*) or experienced business plan writing (*exp_bp*) – both variables measured as percentages per each team – positively correlates with the sole innate effectuation degree: the first is significant

(p<0.01) in models 5.a and 5.b, whereas the second one is significant (p<0.05) in models 1.a and 2.a . Again, this is to give evidence about the prominent experience weight on the effectuation framework, while showing its inferior influence on the natural scientific approach. Finally, despite the positive influence on scientificity into a number of models (1.a-1.b-2.a-2.b), an interesting side effect is that an experience proxy, namely the number of firms previously established by each participant, is strongly (p<0.01) but negatively related to the effectuative nature in models 5.a and 5.b . The phenomenon can be due to the poor numerosity of such variable, given that the records in *av_numestabl* are mostly (>90%) blank values. Instead, in opposition to Vliamos (2012) and Pugliese (2016) who invoked the role of opportunity recognition into the effectuative approach, no evidences arise about the importance of the industry to which the startup belongs, or the sector in which the entrepreneurs declared their experience years.

In conclusion, the seventh research question wanted to examinate potential gender effects onto the decisional processes, by following the large literature present on such topic (Frost et al., 1990; Gatewood et al., 1995; Masson et al., 2003; De Visser, et al., 2010; Apesteguia, 2012; Shepherd, 2012; Stoet et al., 2013; Zhao & Zhang, 2016; Block et al., 2018; Lee & Ashton, 2020). The drivers taken into consideration have been the gender heterogeneity, along with the boolean variables measuring whether the team has female majority (*fem_maj*), female unanimity (*fem_unan*) or at least one female individual (*fem_oneplus*); obviously the male equivalent is symmetrical. Even though the variable *fem_oneplus* demonstrated to be the more relevant into all the regression models - as it could be expected according to the discoveries by Apesteguia (2012) – they did not get significant correlation with dependent variables in any statistical specification. As previously said in prior chapters, only the Blau's gender index showed significant negative correlation with the natural scientific approach (model 5.b.RC), looking like such difference leads worse relationship conflict management which outperforms the benefit coming from a better task conflict management. Anyway, we have to underline that also in this case the p-value is weak (8%). The effect does not keep the same within the specification where effectuation is treated: this is to corroborate that heterogeneity has largely more influence on the structured dynamics of feedback exchange which characterize the scientific paradigm, while are not a central driver for the natural effectuation level.

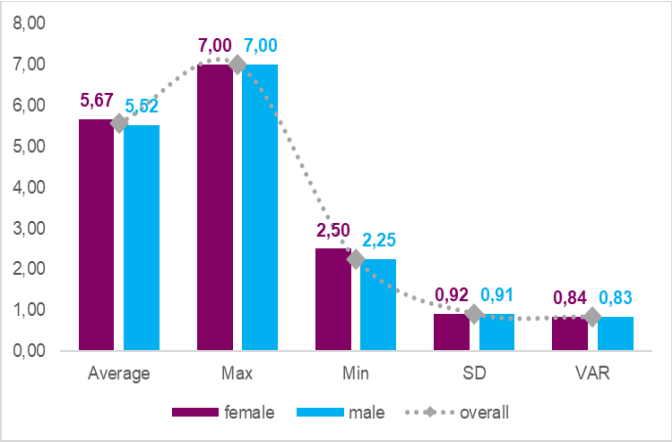

Figure 51: risk appetite stats according to gender

Indeed, the effectuative method pays more attention to enough abstract abilities such as network, control, execution, and

flexibility, less suffering the effect brought by task conflict and relationship conflict management. In addition, no less than the risk appetite aptitude (Stanton et al., 2010; Van den Bos et al., 2012; Orsini et al., 2016; Kluen et al., 2017; Wu et al., 2020) resulted as not correlated with gender, despite it has been studied so far by a lot of researches in medicine, so gathering numerous evidences with accurate biomedical electronic means at diverse levels. They provided explanations by hormonal, instinctual, loss sensitivity and neural standpoint. Please view Figure 51, where every statistical property about risk appetite is completely aligned between female and male entrepreneurs (N=542) – thus again highlighting the lack of gender evidences throughout the experiment of interest. This results perhaps confirms the intuitions proposed by Carr (2010) and Tinkler (2016). The first paper found that decision-making process can be affected by concerns about stereotypes and identity devaluation, rather than attribute gender differences to innate and stable factors. Tinkler instead decided to investigate venture capitalists' funding decisions in high-growth and high-tech entrepreneurship, so discovering that: 1) women received higher evaluation by VCs when the assessment moment happened with close contact; 2) when in presence of technical background of both male and female entrepreneurs, the VC evaluation did not register variations among genders; 3) when technical background was absent and prior performance information ambiguous, the female entrepreneurs received lower evaluations than male non-technical entrepreneurs, therefore women were supposed to be less competent and having less leadership ability when available information was insufficient. These findings thus suggest for gender differences not linked to actual personal features, but rather to prejudices and social inequality; in other words, they warned about a sort of self-fulfilling prophecy at basis of the phenomenon.

According to what shown above, is evident how a certain type of characteristics systematically may have impact on natural scientificity and effectuation degrees belonging to each entrepreneurial team, with a great weight on the decision-making process. In light of the outstanding and superior performances registered by startups applying scientific and effectuative approach – as furnished in literature above all by Camuffo et al. (2017) and Sarasvathy et al. (2001, 2003) – this thesis work brings to conclude that the institutional bodies as well as more technical entities (e.g. government, universities, accelerators, incubators and so on) should promote the most balanced entrepreneurial team compositions by exploiting findings like that, in order to foster the positive impacts that are likely to be observed on decisional activities. The totality of the analyses executed in this thesis work took into consideration a sample composed of 305 mainly Italian startups, with a total of 542 entrepreneurs. Therefore, it could be interesting to replicate the elaboration on a wider sample and consisting of more international composition. Additionally, the work presents limitations and the variance explained by the considered variables should be extended thanks to following researches. For instance, the use of certain industries could be reviewed, so as to increase the numerousness of each sub-category and maybe assign the

startups to different clusters by exploiting a new codification type. Yet, a more in-depth investigation on gender effects could be implemented, trying to corroborate (or invalidate) the surprising findings here detected. Also the psychological capital influence deserves further detailed study, because the not statistical relevance we observed in this work could be due to biases introduced through tendentious questions (proposed in interview/surveys) or could derive from errors by research assistants in assigning marks at time zero, that is likely to happen given the extreme learning economies usually observed in difficult evaluation tasks like that. In conclusion the heterogeneity influence, as well as the ambiguous effects on innate levels of scientificity and effectuation deserve to be further investigated. The moderate and poor composition heterogeneity which was observed through the chosen sample has imposed a large set of unusable Blau's indicators, because it is recognized that low regressors' variance calls for major OLS estimators' variance, so causing important problems for the OLS regression reliability. All this is mostly true in light of the not completely expected strong correlation between the two dependent variables at time zero. Indeed, as evident in Figure 37, the two variables of interest seem to fall on an almost perfect linear approximation, so provoking a kind of uncertainty about the existing differences and similarities. Anyway, it is predictable that the following analyses which are going to be executed throughout all the time touchpoints will lead to different relationships, given that the scanning accuracy level acquired by the RAs is likely to increase with the IVL program evolution.

APPENDIX

Appendix A: main features of Stevens' measurement scales theory

SCALE	EMPIRICAL OPERATION	ADMITTED TRANSFORMATION	CENTRALITY INDICATOR	DISPERSION INDICATOR	CORRELATION	SIGNIFICANCE TEST
Nominal	non-equivalence	permutation	mode value	H information	-	chi-squared
Ordinal	ordering	increasing monotonic functions	median value	fractiles	Spearman correlation	verse
Linear (Interval)	equality between intervals	linear function (e.g. similarity & translation)	arithmetic mean	standard deviation, variance	Pearson coefficient	t-Student, F-Fisher
Linear (logarithm)	equality between ratios	exponents	-	percentage variation	-	-
Ratio	equality between both intervals and ratios	similarity	geometric mean, harmonic mean	-	-	-

	suind_agric	suind_oth	suind_commun	suind_animcare	suind_publishing	suind_electro	suind_energ	suind_finance	suind_food
av_scient	**-0,03162**	**-0,03576**	**-0,03997**	**-0,00463**	**0,090773**	**-0,08242**	**-0,03114**	**-0,00912**	**-0,04901**
av_wscient	**-0,03014**	**-0,04081**	**-0,03713**	**-0,00538**	**0,08822**	**-0,08586**	**-0,03091**	**-0,00329**	**-0,05159**
av_effectuat	**-0,04613**	**0,005136**	**-0,02044**	**-0,05654**	**0,033519**	**-0,12307**	**0,047189**	**0,010052**	**-0,05998**
av_weffectuat	**-0,04928**	**-0,00592**	**-0,02247**	**-0,06704**	**0,030942**	**-0,12211**	**0,05328**	**0,020432**	**-0,04708**
bu_gender	0,039004	0,018111	-0,08047	-0,0338	-0,0338	-0,05371	-0,0338	0,074639	-0,06659
bu_age	-0,07357	-0,05976	-0,07729	0,077972	-0,03246	-0,05159	0,077972	-0,02929	0,017666
bu_region	-0,05141	-0,03409	-0,05401	-0,02268	-0,02268	-0,03604	-0,02268	-0,00119	-0,08526
bu_maxaclvl	0,034952	-0,08571	-0,08981	0,025007	-0,05166	-0,08209	0,063341	-0,02126	0,089806
bu_lvlstu	0,133151	0,10135	-0,07643	#DIV/0!	#DIV/0!	-0,05877	0,133151	-0,07643	-0,04487
bu_othcom	-0,00453	-0,0505	-0,09631	-0,04045	-0,04045	-0,06428	0,095275	0,026017	0,079292
bu_curstude	-0,06682	-0,05328	-0,0702	-0,02948	-0,02948	-0,04685	0,093114	-0,01618	-0,00559
bu_curacbg	-0,03275	0,052193	-0,07432	#DIV/0!	#DIV/0!	-0,05714	0,102658	-0,06622	-0,03394
bu_expbp	-0,05158	-0,03806	-0,09959	0,053516	-0,04183	-0,00587	0,053516	0,0294	0,04607
bu_alrestabl	-0,01025	-0,04809	-0,02282	-0,03089	-0,03089	-0,04909	0,086298	0,08725	0,056458

	suind_educ	suind_hardw	suind_entert	suind_fash	suind_health	suind_induserv	suind_homeserv	suind_sw	suind_transplog	av_age	Center
av_scient	**0,112471**	**0,002974**	**0,085939**	**-0,02404**	**0,007206**	**-0,10744**	**0,056081**	**0,144359**	**-0,10173**	**-0,0118**	**0,13214**
av_wscient	**0,109917**	**0,002911**	**0,086331**	**-0,02416**	**0,013363**	**-0,10696**	**0,054097**	**0,147859**	**-0,10154**	**-0,00985**	**0,127272**
av_effectuat	**0,080926**	**0,020257**	**0,092361**	**0,016444**	**0,04561**	**-0,03035**	**0,006457**	**0,031587**	**-0,11445**	**0,021321**	**0,043301**
av_weffectuat	**0,090758**	**0,010926**	**0,090614**	**0,016015**	**0,051842**	**-0,03069**	**0,00567**	**0,032116**	**-0,12465**	**0,021235**	**0,05099**
bu_gender	0,07762	-0,02386	-0,0396	0,036681	-0,02916	-0,05893	0,004974	0,066514	-0,01848	-0,00935	0,015151
bu_age	0,014273	-0,02292	-0,01726	-0,03708	0,040468	-0,0566	0,005721	0,193224	0,042251	-0,03321	0,080738
bu_region	0,061762	-0,01601	0,080655	0,072275	-0,02835	-0,03955	-0,04279	0,18671	-0,04869	-0,07809	0,113016
bu_maxaclvl	0,024066	0,085308	0,038253	-0,01054	-0,08219	-0,09008	-0,05097	0,258774	-0,03318	-0,02278	0,055858
bu_lvlstu	0,15153	#DIV/0!	-0,08402	-0,03602	-0,04487	-0,04782	-0,06811	-0,00514	-0,06811	0,093209	0,133275
bu_othcom	0,024241	-0,02856	-0,04554	-0,03872	-0,02685	-0,07053	-0,02145	0,201885	0,010279	-0,03534	0,044175
bu_curstude	0,053312	-0,02081	-0,0043	-0,03371	-0,02796	-0,05141	0,018719	0,249102	0,002502	-0,07651	-0,02009
bu_curacbg	0,170448	#DIV/0!	-0,00714	0,065995	-0,03394	-0,04648	-0,05714	-0,05007	-0,06622	-0,17626	0,174359
bu_expbp	0,010797	0,121914	-0,06368	0,033131	-0,05886	-0,07293	-0,07891	0,158023	0,058016	-0,12082	0,022279
bu_alrestabl	-0,04631	-0,02181	0,042861	-0,08149	-0,03648	-0,05386	0,012782	0,117851	0,05247	0,120255	0,062522

	North	South	fem_maj	fem_unan	fem_oneplus	su_numer	av_weekly_hrsxmember	su_phase	su_ph1	su_ph2	su_ph3	su_ph4
av_scient	**-0,03926**	**-0,06903**	**0,030467**	**-0,0361**	**0,082718**	**0,367048**	**0,285792**	**0,30842**	**-0,37357**	**0,231548**	**0,219444**	**-0,03251**
av_wscient	**-0,03589**	**-0,06652**	**0,034751**	**-0,03407**	**0,088871**	**0,373348**	**0,283867**	**0,311159**	**-0,37509**	**0,231469**	**0,219797**	**-0,03281**
av_effectuat	**0,009819**	**-0,09115**	**-0,01914**	**-0,1015**	**0,038134**	**0,412356**	**0,337068**	**0,483904**	**-0,52075**	**0,300823**	**0,21458**	**0,095832**
av_weffectuat	**0,008265**	**-0,09253**	**-0,01906**	**-0,09964**	**0,039949**	**0,415243**	**0,33176**	**0,482647**	**-0,52333**	**0,304835**	**0,218785**	**0,089532**
bu_gender	0,068068	-0,08281	0,443253	-0,16395	0,658559	0,364106	0,021943	-0,02717	0,061566	-0,09509	0,061105	-0,05893
bu_age	-0,06161	0,013628	0,047289	-0,09868	0,209147	0,362993	0,056835	0,180848	-0,14892	-0,00536	0,185342	0,015604
bu_region	-0,09443	0,062691	-0,03106	-0,06804	0,037592	0,180408	-0,03428	0,028771	-0,10915	0,106432	0,104325	-0,03955
bu_maxaclvl	-0,03634	0,025625	0,111864	-0,13268	0,2514	0,449247	0,140585	0,070206	-0,07867	0,040453	0,053382	-0,00235
bu_lvlstu	-0,11438	0,004203	0,207687	-0,1123	0,219822	0,383626	0,005947	-0,05342	0,052792	-0,05569	0,03474	-0,04782
bu_othcom	-0,04346	0,040779	0,046428	-0,12664	0,171884	0,356883	0,094603	0,057274	-0,08048	0,01831	0,120638	0,047793
bu_curstude	-0,01395	0,037683	0,068128	-0,08137	0,15496	0,305799	0,014359	0,041232	-0,07558	0,021133	0,153491	-0,05141
bu_curacbg	-0,06308	-0,07583	-0,06975	-0,16683	0,077066	0,243988	0,053211	0,043628	-0,10535	0,112691	0,052916	-0,04648
bu_expbp	-0,03126	0,043163	0,041291	-0,05908	0,12784	0,329156	0,054194	0,081671	-0,12872	0,098021	0,082254	-0,01059
bu_alrestabl	-0,04041	-0,03437	0,130137	0,002661	0,270674	0,260972	0,105833	0,1326	-0,07567	-0,06325	0,131486	0,080229

Appendix B: extract from correlation matrix – part I

su_ph5	prod_offer	serv_offer	bothcomb_offer	av_weekly_hrsonsu	av_aclvlyrs_biased	maj_currstem	maj_curreco	maj_curroth	rep_currstem	rep_curreco	rep_curroth	av_aclvlyrs_right	av_workexpyrs	av_workexpyrs_suind	av_numindustries_exp	av_execyrs	alr_establ	av_numestabl	exp_bp	ecomgt_crs	entrep_crs	av_vert1	av_horiz1	av_vert2	av_horiz2	intern_netw	diff_quality	diff_design	diff_usab	diff_prco	diff_oth
0,145616	-0,21915	0,191431	0,03242	0,256027	-0,04603	-0,03643	0,027645	-0,04099	-0,12777	0,013743	-0,03425	0,155474	0,003791	0,066007	0,188068	0,087582	0,134203	0,157027	0,151786	0,164739	0,134344	0,035525	0,086524	0,039259	0,193386	0,288977	0,074068	-0,03916	0,134157	0,070259	0,025482
0,148959	-0,22311	0,195805	0,031231	0,252668	-0,04429	-0,0373	0,026843	-0,03811	-0,12822	0,011623	-0,03266	0,163315	0,004894	0,067642	0,187407	0,089384	0,133433	0,157389	0,151731	0,170593	0,135311	0,036235	0,092232	0,044118	0,199655	0,295848	0,075087	-0,03779	0,139324	0,066539	0,022201
0,268506	-0,12027	0,073972	0,078093	0,311536	-0,06366	-0,04311	-0,02752	0,018263	-0,11608	-0,03523	0,051956	0,146496	0,025756	0,109892	0,226163	0,098749	0,152604	0,117532	0,218736	0,136198	0,067191	0,066797	0,117895	0,060414	0,185974	0,30875	0,079782	0,063502	0,072624	0,07926	-0,02415
0,265479	-0,11055	0,064211	0,079133	0,304049	-0,05514	-0,04184	-0,02111	0,0218	-0,11408	-0,02978	0,053969	0,156501	0,023888	0,106861	0,236582	0,102733	0,162336	0,124302	0,220707	0,146507	0,065123	0,064962	0,118846	0,056154	0,190645	0,313716	0,087231	0,063085	0,070252	0,079942	-0,02374
0,001653	-0,01465	0,049288	-0,06863	-0,05227	-0,00699	0,023367	-0,00659	-0,06464	-0,011	0,015893	-0,05685	0,166056	-0,04348	-0,02722	-0,06754	-0,04302	-0,01139	-0,02202	0,043138	0,09294	0,04506	0,048535	0,085402	0,089219	0,115744	0,238754	-0,0226	0,014485	0,067514	-0,01918	0,048453
0,098698	-0,08325	0,07621	0,005549	-0,05255	0,013723	0,102686	-0,05525	-0,02462	-0,01064	-0,05383	0,030915	0,17969	-0,06938	0,028006	-0,00166	-0,04064	0,013775	0,006317	0,052648	0,074375	0,005747	0,153152	0,134266	0,091162	0,166718	0,235392	-0,0133	-0,0471	-0,00291	-0,01299	0,081418
-0,06125	-0,12426	0,156267	-0,07398	-0,04292	0,063647	0,02032	0,116828	-0,01923	-0,0586	0,046777	-0,00853	0,107586	-0,06706	-0,05768	-0,01775	-0,06657	-0,08667	-0,07416	-0,00521	0,002485	0,040206	0,089754	0,12191	0,064471	0,074023	0,165992	0,001873	0,019559	0,079731	-0,00096	0,007502
0,034246	-0,10486	0,128443	-0,05596	0,053444	-0,02551	0,126647	-0,07405	-0,01028	0,048963	-0,10657	-0,03513	0,230734	-0,09131	0,010425	-0,06541	-0,11294	-0,06262	-0,05601	-0,00145	0,052116	0,042876	0,129097	0,149854	0,105715	0,147051	0,352122	0,057953	-0,02086	-0,00584	0,025126	0,059165
-0,04782	-0,06599	0,104433	-0,09109	-0,02239	0,088367	0,1229	-0,11433	0,023707	0,055097	-0,05768	-0,01517	0,18424	0,001002	-0,00536	-0,02257	-0,04293	-0,00462	-0,0065	0,043821	0,083053	-0,03352	0,085592	0,140779	0,024824	0,113979	0,263669	-0,09981	-0,00848	-0,02386	-0,04791	0,03924
-0,03942	-0,05844	0,037949	0,034056	0,065275	0,106816	0,228562	0,011039	-0,06035	0,113725	-0,02277	-0,0844	0,13774	-0,08	0,046808	-0,06879	-0,02471	-0,04502	-0,03398	0,044844	0,101023	0,043554	0,129433	0,11741	0,093901	0,115116	0,322769	-0,00167	-0,02238	0,068624	0,066768	0,033572
-0,03232	-0,01987	0,022066	-0,00619	-0,03602	0,097068	0,190669	0,045855	-0,04748	0,047749	0,003489	-0,04101	0,140478	-0,12956	-0,05696	-0,07844	-0,10426	-0,06301	-0,065	0,063498	0,068162	0,036354	0,115011	0,083189	0,103212	0,113132	0,218755	-0,02154	-0,10134	0,059184	-0,02927	-0,00311
-0,04648	-0,12329	0,159593	-0,0886	-0,00822	-0,02278	0,120393	-0,12874	0,183934	0,040048	-0,08091	0,001396	-0,0254	-0,11657	-0,12148	0,008471	-0,09743	-0,10822	-0,09534	-0,12094	-0,14221	-0,10355	0,078425	0,000749	-0,03646	-0,06186	0,082855	0,050746	0,0158	0,056173	0,033012	0,050706
0,006583	-0,07071	0,101413	-0,06644	-0,04126	0,068217	0,081959	0,064893	0,042419	0,036634	0,022651	-0,04779	0,175509	-0,14352	-0,01473	-0,03166	-0,10006	-0,10189	-0,0879	-0,03397	0,108467	0,071367	0,162191	0,147841	0,112111	0,108393	0,270673	0,074559	-0,0548	0,103884	0,005747	0,110628
0,06914	-0,09112	0,094154	-0,01475	0,019142	-0,11908	-0,05529	-0,06301	-0,00995	-0,07379	-0,06164	-0,04174	0,158038	0,086764	0,149305	0,061769	0,067709	0,25425	0,205573	0,089147	0,082746	-0,00214	0,090317	0,135402	0,03627	0,154133	0,319648	0,008317	-0,06211	-0,01442	0,064403	0,036123

Appendix B: extract from correlation matrix – part II

av_rlvncprco	av_rlvncquality	av_rlvncusab	av_rlvncdesign	av_rlvncoth	av_selfesteem	av_riskappet	av_novelty	av_planner	av_firstline	av_lgo	av_pao	av_pgo	av_perforient	av_rich	av_career	av_solveident	av_shapeident	av_socialprob	av_world	av_robust	av_deeplyan	av_supplyident	av_agree	av_wrldctzn	av_wrldplc	av_compet	av_advcompet	av_focusident	av_supident	av_social	av_persuade	av_teambuild
0,001424	**-0,00349**	**0,03202**	**0,000703**	**0,029015**	**0,100744**	**0,077748**	**-0,0398**	**-0,01265**	**0,019147**	**0,041737**	**-0,03558**	**-0,12074**	**-0,08381**	**-0,09404**	**-0,08918**	**0,099411**	**0,139001**	**0,050376**	**0,04649**	**-0,05759**	**-0,0819**	**0,050808**	**0,114083**	**0,001796**	**0,01859**	**-0,0199**	**0,046343**	**0,106649**	**0,092974**	**-0,0001**	**-0,03604**	**0,157705**
-0,00186	**-0,00733**	**0,035097**	**-0,00013**	**0,028262**	**0,101959**	**0,078315**	**-0,04063**	**-0,01088**	**0,021472**	**0,038837**	**-0,03864**	**-0,12216**	**-0,08626**	**-0,09513**	**-0,09151**	**0,102005**	**0,142299**	**0,053061**	**0,049368**	**-0,05806**	**-0,08481**	**0,054205**	**0,11746**	**0,003599**	**0,017436**	**-0,01947**	**0,045229**	**0,109166**	**0,096417**	**0,00256**	**-0,04193**	**0,156465**
0,106692	**0,007986**	**0,020647**	**0,079529**	**0,069535**	**0,169794**	**0,028126**	**-0,02829**	**-0,05145**	**-0,06026**	**-0,03511**	**-0,08834**	**-0,15342**	**-0,13693**	**-0,1159**	**-0,10923**	**0,14019**	**0,165368**	**0,04636**	**0,022313**	**-0,05915**	**-0,12282**	**0,100908**	**0,11749**	**0,032335**	**0,028912**	**-0,00556**	**0,059893**	**0,152505**	**0,152535**	**0,021306**	**-0,01559**	**0,184885**
0,108299	**0,006904**	**0,009487**	**0,076754**	**0,064322**	**0,177458**	**0,032681**	**-0,02255**	**-0,04187**	**-0,05158**	**-0,0265**	**-0,08797**	**-0,15528**	**-0,13705**	**-0,10863**	**-0,10841**	**0,137823**	**0,166571**	**0,035703**	**0,023219**	**-0,05131**	**-0,11498**	**0,101581**	**0,119618**	**0,02985**	**0,027471**	**-0,00234**	**0,061691**	**0,145512**	**0,145108**	**0,017035**	**-0,02028**	**0,190224**
-0,01062	0,061258	0,061075	0,051797	0,00506	0,014586	-0,04522	-0,06715	0,02728	-0,02294	-0,02843	0,011992	0,078655	0,059426	0,037471	0,048831	-0,08913	-0,02036	-0,01919	-0,04193	-0,03063	-0,0647	-0,0298	-0,03167	0,012698	-0,00315	0,014165	0,015298	0,002193	-0,02609	0,000666	0,015538	0,175433
-0,04226	0,01682	0,047689	0,031606	0,06305	0,043427	-0,02991	-0,02036	0,029643	-0,04406	-0,04831	0,023582	0,125346	0,097908	-0,12156	-0,07789	-0,02504	0,002886	0,070882	-0,00217	-0,02828	-0,10528	-0,03221	0,037256	-0,02206	-0,01476	0,032897	0,005138	0,04191	0,023963	-0,00597	0,007173	0,138817
-0,03791	0,040322	0,065481	0,019332	-0,00661	-0,03649	-0,02189	-0,02661	0,028539	-0,01235	-0,0209	0,049222	0,050032	0,059955	-0,07183	-0,04061	0,042911	0,101812	0,044012	0,037628	0,028746	-0,03517	0,049494	0,065639	0,045336	0,022973	0,025866	-0,03459	0,080487	0,069954	-0,03463	-0,00553	0,068607
0,00184	0,044244	0,062568	-0,00407	0,039255	0,020276	-0,06332	-0,10431	-0,00787	-0,0476	-0,1069	-0,05221	0,096048	0,033059	-0,03677	-0,06818	-0,12086	-0,06417	-0,04898	-0,12421	-0,08083	-0,13947	-0,10344	-0,08434	-0,06995	-0,10425	-0,02951	-0,04797	-0,03888	-0,07739	-0,15609	-0,06492	0,200046
-0,09233	-0,05218	-0,05859	-0,07324	-0,03748	0,045888	-0,08803	-0,07468	0,007066	-0,07172	-0,04298	-0,02777	0,103183	0,046899	-0,04169	-0,06915	-0,07207	-0,0265	0,006354	0,030688	-0,04616	-0,10296	-0,03941	-0,00413	0,0389	0,01233	-0,07083	-0,04705	0,053846	0,025194	0,073779	0,01572	0,145608
-0,00967	0,045245	0,048608	0,015552	-0,01385	0,048647	-0,04498	-0,01926	0,054047	-0,01964	-0,05199	0,040614	0,098796	0,092458	-0,03928	-0,02401	-0,08017	-0,03735	-0,03302	-0,0481	-0,0115	-0,06584	-0,05047	-0,03368	0,01319	-0,01738	0,01902	-0,00156	-0,03403	-0,0475	-0,06473	0,029705	0,17712
-0,06682	0,053265	0,048526	0,037532	0,000916	0,029765	-0,02286	-0,02741	0,032277	-0,0815	-0,06814	0,057027	0,096558	0,099649	-0,03929	0,006799	-0,07384	-0,02836	-0,008	-0,05977	-0,03861	-0,11457	-0,05897	-0,01908	-0,04542	-0,04827	0,016708	-0,01715	-0,05042	-0,05162	-0,06923	0,015987	0,101615
0,032963	0,06447	0,066037	-0,08808	-0,01957	0,037678	-0,03694	-0,04487	-0,12484	-0,12734	-0,02792	0,056043	-0,00804	-0,00707	0,042231	-0,00281	-0,10946	-0,02269	-0,13461	-0,08987	-0,10796	-0,07873	-0,13466	-0,14944	-0,08064	-0,04428	-0,0674	-0,11716	-0,01319	-0,00136	-0,04388	-0,12965	0,10167
0,016178	0,052805	0,095033	0,034278	0,036733	0,060546	-0,00606	-0,09089	0,013305	-0,04293	-0,035	0,061588	0,085943	0,076811	0,038085	0,013467	-0,13788	-0,05274	-0,05267	-0,11818	-0,10369	-0,10116	-0,13334	-0,07386	-0,0843	-0,11074	-0,0086	-0,03025	0,00467	-0,04379	-0,12218	-0,06101	0,154669
0,040264	0,016973	0,04973	-0,01222	0,073992	0,094824	-0,00816	-0,0603	-0,0342	-0,02288	-0,06247	-0,04	0,048981	0,012943	-0,0297	-0,02879	0,004422	0,012559	-0,01739	-0,05004	-0,02472	-0,05182	0,006068	0,017872	-0,01139	-0,01178	0,026938	-0,01594	0,040523	0,032846	-0,05061	-0,00163	0,148241

Appendix B: extract from correlation matrix – part III

Appendix C: recap of all the regression models – part I

Legend: ^ p<15% (alert, no relevant statistical significance) ; * p<10% ; ** p<5% ; *** p<1%

			number of obs	Fisher		Prob > F	R-squared	Root MSE	suind_agric		suind_oth		suind_commun		suind_animcare		suind_publishing		suind_electro		suind_energ		suind_finance		suind_food		suind_educ		suind_hardw		suind_entert		suind_fash		suind_health		suind_induserv		suind_homeserv		suind_sw		suind_transplog		av_age		Center		North		South		fem_maj		fem_unan		fem_oneplus	
5.a	gen	scient	298	F(34,244)	\	\	0,4110	0,94134							-	*	+	***			-	**					+	**	+	***											-	**												
		effectuat	298	F(34,244)	\	\	0,5182	0,64365							-	***					-	*							+	***											-	***					-	*						
5.b	gen + ac_lvl	scient	298	F(41,237)	\	\	**0,4296**	**0,93998**									+	***			-	**					+	**	+	***																	-	^						
		effectuat	298	F(41,237)	\	\	**0,5433**	**0,63583**							-	***					-	**							+	***											-	***					-	*						
1.a	1° model - no control	scient	305	F(10,294)	6,76	0	0,1551	1,0398																																															
		effectuat	305	F(10,294)	7,06	0	0,1739	0,77945																																														
1.b	1° model - yes control	scient	305	F(11,276)	\	\	0,2990	0,97758									+	***			-	***					+	*	+	***							-	*																
		effectuat	305	F(11,276)	\	\	0,3523	0,71235							-	***	+	***	-	*					-	^			+	***											-	*												
2.a	2° model - no control	scient	305	F(17,287)	5,82	0	0,2067	1,0198																																														
		effectuat	305	F(17,287)	5,77	0	0,2112	0,77091																																														
2.b	2° model - yes control	scient	305	F(19,268)	\	\	0,3209	0,97645					-	^			+	***			-	**					+	^	+	**							-	^																
		effectuat	305	F(19,268)	\	\	0,3730	0,71124							-	***	+	^	-	^					-	^			+	**											-	^												
3.a	3° model - no control	scient	302	F(8,276)	\	\	0,1760	1,0546									+	***	-	^	-	***					+	*			+	^					-	**			+	^	-	**										
		effectuat	302	F(8,276)	\	\	0,1279	0,82599							-	***			-	**	+	^			-	^			+	^													-	***										
3.b	3° model - yes control	scient	298	F(20,260)	\	\	0,3122	0,98544							-	*	+	***			-	***					+	^	+	*							-	**																
		effectuat	298	F(20,260)	\	\	0,3609	0,71813							-	***	+	*	-	^					-	^			+	***											-	*	-	*										
4	4° model	scient	298	F(20,277)	4,94	0	0,2725	0,98191																																														
		effectuat	298	F(20,277)	7,52	0	0,3207	0,71729																																														

su_numer	av_weekly_hrsxmember	su_phase	su_ph1	su_ph2	su_ph3	su_ph4	su_ph5	prod_offer	serv_offer	bothcomb_offer	av_weekly_hrsonsu	av_aclvlyrs_biased	maj_currstem	maj_curreco	maj_curroth	atleast1_stemeco	rep_currstem	rep_curreco	rep_curroth	av_aclvlyrs_right	av_workexpyrs	av_workexpyrs_suind	av_numindustries_exp	av_execyrs	alr_establ	av_numestabl	exp_bp	ecomgt_crs	entrep_crs	av_vert1	av_horiz1	av_vert2	av_horiz2	intern_netw
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Appendix C: recap of all the regression models – part II

Legend: ^ p<15% (alert, no relevant statistical significance) ; * p<10% ; ** p<5% ; *** p<1%

diff_quality	diff_design	diff_usab	diff_prco	diff_oth	av_rlvncprco	av_rlvncquality	av_rlvncusab	av_rlvncdesign	av_rlvncoth	av_selfesteem	av_riskappet	av_novelty	av_planner	av_firstline	av_lgo	av_pao	av_pgo	av_perforient	av_rich	av_career	av_solveident	av_shapeident	av_socialprob	av_world	av_robust	av_deeplyan	av_supplyident	av_agree	av_wrldctzn
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Appendix C: recap of all the regression models – part III

Legend: ^ p<15% (alert, no relevant statistical significance) ; * p<10% ; ** p<5% ; *** p<1%

av_wrldplc	av_compet	av_advcompet	av_focusident	av_supident	av_social	av_persuade	av_teambuild	av_scient	av_effectuat	bu_gender	bu_age	bu_region	bu_maxaclvl	bu_maxaclvl_nophd	bu_lvlstu	bu_othcom	bu_curstude	bu_curacbg	bu_expbp	bu_alrestabl	bsc_maj	msc_maj	master_maj	nothing_maj	phd_maj	bsc_ing_maj	msc_ing_maj	master_ing_maj	postlaur_ing_maj
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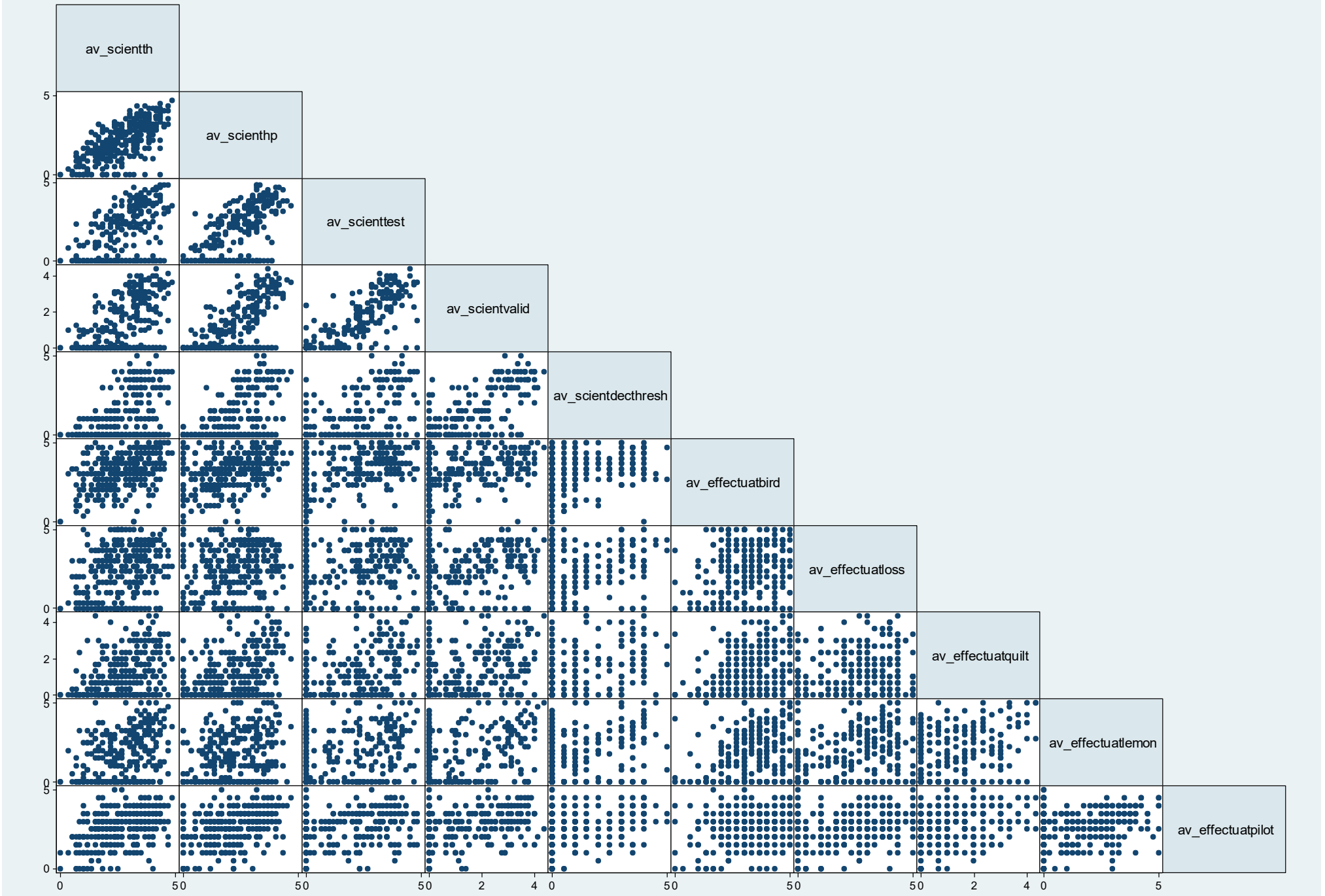
Appendix C: recap of all the regression models – part IV

Legend: ^ p<15% (alert, no relevant statistical significance) ; * p<10% ; ** p<5% ; *** p<1%

Appendix D: crossed scatter plots referred to the sub-variables of interest



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