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Regular Article

From explanation of the past to prediction of the future: A comparative and predictive research design in the Social Sciences

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ABSTRACT

Business and Psychology research (and the Social Sciences, in general) is heavily biased toward explaining the past. The holy grail in such explanation-oriented research is to develop causal theory, and to test this theory with historical data against a null no-effect benchmark. We seek to expand the methodological toolkit by adding a comparative and predictive research design. First, by organizing an inter-theory battle, we move away from classic null hypothesis testing. Second, by predicting the future, we add prediction as a complement to the traditional explanation of the past. By way of illustration, we select a case in the Entrepreneurship field and theorize about the ranked predictions as to the relative growth performance of a sample of Small and Medium-sized Enterprises (SMEs). For this, we adopt two widely acknowledged theories in the literatures of Business and Psychology: The Competitive Strategy theory and the Motive Disposition theory. We use Gamblers' Ruin or Random Walk theory, arguing that company growth cannot be predicted, as the null benchmark. After identifying key explanatory predictive variables of our basic pair of theories, with Gamblers' Ruin or Random Walk theory's non-predictability as our benchmark, we produce ranked predictions as to the relative growth performance of 294 Belgian entrepreneurs and their SMEs. Later in 2023, we will test the predictive accuracy of these two selected theories and their predictive variables by comparing the predictive rankings with realized growth, as well as vis-à-vis randomness.

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1. Introduction

Historically, Business and Psychology research (as is the case for most research in the Social Sciences) is heavily biased toward the explanation of past events. The holy grail in such postdictive explanation-oriented research is to develop causal theory, and to test this theory with historical data against a null no-effect benchmark. Good theory provides a convincing explanation of outcomes by spelling out the underlying causal chain. This causal chain may be simple, identifying critical direct effects, or can be complicated, detailing a model with mediation and/or moderating relationships. To unravel causality, the ideal of a randomized controlled trial is oftentimes simply out of reach. Instead, sophisticated econometric identification strategies are applied to noisy longitudinal historical field data. A theory's hypothesis is said to be confirmed if a test vis-à-vis the null hypothesis is statistically significant (and of the correct sign, of course) – i.e., gives a *p* value below

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a critical rule-of-thumb threshold (usually .05).

Take the simple example of the human capital theory applied to the field of Entrepreneurship. This theory convincingly argues that an entrepreneur's education and experience explain different entrepreneurial outcomes, such as entry and performance. For instance, van Praag et al. (2013) analyze a large US representative panel dataset to show that entrepreneurs have higher returns to formal education than employees, estimating a series of income equations using sophisticated instrumental variables methodology. However, and this is typical for the domain of Social Sciences, the test of the theory is on historical data. And, as is standard in our domain, too, is that all the theory's hypotheses are tested against the no-effect null. This implies that, in essence, the predictions of the theory are tested by explaining the past better vis-à-vis randomness.

We do not argue that this empirical strategy is useless – absolutely not. Theories that explain the past better than randomness are the bread and butter of our domain, and for good reasons. And luckily, the days of cross-section tests of causal theories are long gone. Rich longitudinal data, often of the panel type, are common by now, as is the application of advanced causality-identification econometrics. This is very good news. However, in the current pre-registration paper, we seek to expand the methodological toolkit by adding a comparative predictive research design. In line with Hofman et al. (2017), we argue that prediction deserves a complementary place next to explanation. As they argue, 'Historically, social scientists have sought out explanations of human and social phenomena that provide interpretable causal mechanisms, while often ignoring their predictive accuracy' (p. 486). Below, we argue in greater detail why we believe prediction of the future should receive an honorable place in Business and Psychology (and the Social Sciences, more broadly), next to explanation of the past (e.g., Parker, 2018). This is not only because predictive accuracy per se is a worthy bonus of scholarly work, but also since prediction is an extra test of a theory's explanatory power: A theory that is not only providing a good explanation of the past, but also offers an accurate prediction of the future, is to be preferred to one that explains history well but cannot predict the future.

Moreover, we move beyond the traditional theory-less null benchmark in two ways. First, we make use of an explicit and substantive theory of randomness. We do so in the context of firm growth. That is, we will develop a case in the Entrepreneurship field where our null is based on recent research results backing the idea that growth is a 'random walk', as already expressed in the classic work of Gibrat (1931). The latest refinement of this idea is Gambler's Ruin theory (e.g., Coad et al., 2013), which argues that past company performance is no or a poor predictor of future results. Second, we pitch two alternative growth theories not only against this theory-rich null, but also against each other. In so doing, we organize inter-theory competition, which is methodologically superior to the standard, and rather meaningless, theory-versus-null battle (Conradie et al., 2019). For a wide variety of reasons, null hypothesis testing is sub-optimal, at best (Starbuck, 2016; van Witteloostuijn, 2019). One reason is that p value statistics are widely misunderstood, and hence routinely misused (van Witteloostuijn, 2020; Wasserstein et al., 2019). Another is that data that are purposely collected to prove that theory X is right, which is common practice, give X an a priori competitive advantage in the battle vis-à-vis the null (Conradie et al., 2019).

In all, our comparative predictive design implies killing three birds with one stone: (1) We offer a predictive research design as a complement to historical explanation; (2) we suggest a powerful comparative battle of theories, beyond the biased and meaningless null test; and (3) we improve upon our current research practices to fight the 'reproducibility crisis'. Together, this would increase the value of our research for practice, as well as offering a strategy to counter common questionable research practices, such as p hacking and HARKing (Meyer et al., 2017), which form the roots of the so-called 'replicability crisis' (van Witteloostuijn, 2016). So, this paper is deeply methodological. Of course, we introduce topic-relevant theories to illustrate our design. We will select two theories from Business and Psychology and apply these to the Entrepreneurship field, from which we select the benchmark theory. After all, the proof of the pudding is in the eating. However, up-front, we want to emphasize that we aim to contribute to methodology, and that we not seek to satisfy the, we believe, counterproductive (and obsessive) requirement to offer 'groundbreaking theoretical novelty' (cf. Birkinshaw et al., 2014; Starbuck, 2016; Tourish, 2019). This is why we first present both pillars of the research design we propose here – comparison and prediction – before we introduce our theoretical (and empirical) workhorses in a case in the Entrepreneurship field.

2. A comparative design

According to 20th century's leading Philosophy of Science, the latter is to be conceived as a battle of competing theories. This is the core of the argument of, e.g., Thomas Kuhn, Imre Lakatos, and Karl Popper. Take the example of Popper, probably the most influential of all. Different theories T_i of a common explanandum Y (say, firm growth), but offering a different explanans X (say, environmental dynamism X_1 in T_1 versus individual self-efficacy X_2 in T_2), compete for the gold medal, with the yardstick being their explanatory power. The Popperian scientific method implies that we design empirical studies aimed to falsify our theory. Each time the theory is not falsified, this theory survives in the world of scientific battles. Strikingly, in Social Sciences, academia adopted the close-to-obligatory practice to test each theory T_i in isolation against a so-called null hypothesis, or null theory T_0, to find support for the theory T_i's hypotheses.

This implies that we, in the Social Sciences, tend to adopt three counter-Popperian practices that frustrate the accumulative progress of knowledge. First, all theories compete against the same fictive 'theory' of no effect – i.e., of the theory that there is no theory – rather than a substantive alternative theory. In this way, current practices imply that we fail to systematically organize inter-theory battles, where we directly test the explanatory power of a theory T_1 against that of an alternative theory T_2 (cf. Conradie et al., 2019). Second, the statistical significance notion is misused to provide 'evidence' that 'supports' a theory's hypotheses (van Witteloostuijn, 2020). We routinely accept hypotheses if the p value is below a magical threshold x (normally 0.05), and hence argue that our study's evidence 'confirms' or 'supports' our theory. Not only is any p value threshold arbitrary, but also does this fundamentally violate the very idea of falsification. Third, in line with the above, we search for certainty where we should accept uncertainty (Brodeur et al., 2015). In the words of Popper (1945a, p. 163), 'the whole secret of the scientific method is readiness to learn from mistakes'. That is, 'the fact that all tests of a theory are attempted falsifications of predictions derived with its help, furnishes the clue of the scientific method' (Popper, 1945b, p. 260).

The bottom line is not only, as convincingly explained by many, like the statisticians Wasserstein and Lazar (2016), and Amrhein et al., (2019), the former Chief Editor of the *Administrative Science Quarterly* Bill Starbuck (2016), and many others advocating against the publication bias (e.g., Andrews & Kasy, 2019; Brodeur et al., 2015), that this is a meaningless exercise that undermines the systematic accumulation of knowledge, but also that this gives rise to wicked misunderstandings, many implying questionable research practices– albeit oftentimes unknowingly, our community being deeply indoctrinated with the belief that our practices are right. This is not the place to discuss these issues in detail. The work of the well-known epidemiologist Ioannidis (e.g., 2005, 2008) is very telling. In fact, the academic community's misuse of statistics in combination with perverse incentives (as reflected in the publication war) are argued to have led to replicability and retraction crises (e.g., Baker, 2016; Fanelli, 2018). As a community, we publish many false positives, we file negatives in the drawer, we do not replicate, and we engage in a series of questionable research practices, varying from salami slicing and data fabrication to HARKing and p-hacking. Essentially, against the spirit of Popper's philosophy, we

create a fiction of a series of unique *p* value certainties, whilst we should rather look uncertainty right in the face to really learn from our unavoidable mistakes (Bosma & van Witteloostuijn, 2021; van Witteloostuijn, 2020).

To counter all this, we should change our research practices by adopting stricter research guidelines (Meyer et al., 2017), by moving toward open science (Beugelsdijk et al., 2020), by conducting many replication studies (Walker et al., 2019), by systematically engaging in inter-theory battles (Conradie et al., 2019), and by applying uncertainty-embracing statistical practices (van Witteloostuijn, 2019, 2020). The research design we introduce in the current paper is in line with these measures, being one that is devoid of many of these counterproductive side-effects of our dominant research practices. Specifically, the first pillar of our research design is inter-theory comparison: We organize an explicit battle between substantive theories (cf. Conradie et al., 2019), and we do not use the meaningless no-effect null benchmark (see, e.g., Starbuck, 2016). So, we do not only formulate a substantive null theory T_0, but we also test a meaningful theory T_1 against another meaningful theory T_2 (and both against T_0). We illustrate our research design for the case of explanandum firm growth, taking the examples of three substantive theories offering a different explanans: the Gambler's Ruin or Random Walk (T_0), competitive strategy (T_1), and motive disposition theories (T_2).

3. A predictive design

The second pillar of our novel research design involves prediction. As Popper (1945b, p. 261) explained, 'theories have several connected tasks. They help to explain as well as to *predict* events' (italics added), and rightly so. It is commonly accepted that scientific knowledge has three power types: Descriptive, explanatory, and predictive. Depending on the area of investigation, researchers tend to favor one of these (Shmueli, 2010). Indeed, prediction is part of the daily bread and butter in the Medical Sciences and Physical Sciences. For whatever reason, in the Social Sciences, a dominant preference for explanatory power is omnipresent, with a close-to-full ignorance of prediction. Browsing through issues of top outlets such as the *Academy of Management Journal* or the *Journal of Business Venturing* is a revealing experience, as the number of studies that focus on predicting the future, rather than explaining the past, is (close to) zero. And expanding the search for predictive studies in other Business and Psychology journals will not produce many more, if any, hits, as also pinpointed in editorials of, for instance, leading entrepreneurship journals (e.g., Anderson et al., 2020). Of course, there is nothing wrong with a quest for (causal) explanation – absolutely not. However, to add prediction, next to description and explanation, to what we do in Social Sciences is important for at least three reasons.

First, prediction is important per se. A theory that explains history well, but has nothing meaningful to say about the future cannot credibly inform firm strategies or governmental policies. Hence, such a theory is impotent with regard to contributing to the solution of current-day and future problems within enterprises and societies. In light of the ongoing relevance-versus-rigor debate (see, e.g., Gulati, 2007), an evergreen in our domain indeed, this does not bode well for the societal legitimacy of Social Sciences studies. The Responsible Research for Business and Management (RRBM) grassroots movement, for example, precisely argues that, as a discipline, Business and Management should take the relevance issue much more seriously (see https://rrbm.network; Tsui, 2017). This is resonated in the pleas for solution-oriented research, which directly contributes to handling the challenges of the future of people, organizations, and societies (Watts, 2017).

Second, the predictive value of studies in Social Sciences is often directly associated with their explanatory power: A good *explanation* is repeatedly considered to also hold value for a good *prediction*. However, from the large literature in a field such as Econometric Forecasting, we know very well that this can only be the case in a world without structural breaks (Castle et al., 2010; Pesaran et al., 2006). In this paper, we critically evaluate this with a case in the Entrepreneurship field, and test whether – to our knowledge for the very first time – variables derived from explanatory theories in Business and Psychology also hold promise for prediction in the Entrepreneurship field. This exercise does not only allow us to critically examine the predictive power of explanatory theories, but also implies that we can fine-tune and extend theories currently used in explanatory settings to perform better in the context of predictive designs. Specifically, we will formulate predictions using insights from three well-established explanatory theories (that is, two basic theories, and one benchmark theory), which we will afterwards (that is, later in 2023; see below) test against actual outcomes. This approach complements advanced explanatory techniques, such as machine learning (e.g., Kolkman et al., 2019; Kolkman & van Witteloostuijn, 2019; van Witteloostuijn & Kolkman, 2018), where large historical datasets are combined with theory to produce explanatory insights and/or predictions.

Third, and most importantly in the context of this paper's central argument, (comparative) prediction is a very powerful test of theories in the spirit of the Popperian Philosophy of Science. As indicated above, we compare the predictive performance of two explanatory theories T_1 and T_2 not only vis-à-vis one another, but also against a substantive no-effect theory T_0. Using historical information regarding variables associated with T_1 and T_2, we predict the enterprises' future performance in the form of a ranking. Regarding our T_0, employment growth has been described as a largely *unpredictable* random walk, in the spirit of Gibrat (1931; see also Sutton, 1997; Caves, 1998), in Gambler's Ruin Theory, as argued in Entrepreneurship studies such as Coad et al. (2013), Derbyshire and Garnsey (2014), Coad et al. (2016), van Witteloostuijn and Kolkman (2018), and Coad et al. (2018). In our future evaluation of actual performance of SMEs, we will thus test the predictive power of the below-developed predictive rankings of T_1 and T_2 not only vis-à-vis one another, but also against T_0's randomness of firm growth. If, by then, both or either one of our predictive rankings turn out to be superior to randomness, we will have shown that our selected explanatory theories (and variables) also hold value for predictive designs. If this is not the case, we can further legitimize the random walk idea in the Popperian sense – i.e., the predictive theories have been falsified, but future ones may survive a next test.

4. An entrepreneurship case: predicting entrepreneurial growth

Our focus is on predicting employment growth of SMEs. This focus is not only of interest for policymakers, but is also – from a theoretical point of view – of interest from the perspective of the Entrepreneurship field, which is thus the field where our case fits to. As said above, we use two well-known theories of Business and Psychology to develop predictive ranking as to employment growth of SMEs. For case selection, we follow ambitious entrepreneurship scholars advocating for gaining additional theoretical insights that facilitate predicting entrepreneurial growth (e.g., Hermans et al., 2015; Shane, 2008). We use job creation as (high) growth indicator. Indeed, the Global Entrepreneurship Monitor (GEM) initiative utilizes expected employee growth to compute the High-Expectation Total Entrepreneurial Activity (HE-TEA) rate (Autio, 2007), and the Panel of Study of Entrepreneurial Dynamics (PSED) takes the number of employees as an indication for preferred company size (Cassar, 2006, 2007; Edelman et al., 2010). In the Discussion, we briefly reflect on other performance metrics, such as profit and sales growth, and survival.

We confront three theories, of which two are non-random theories of company growth in the domains of Business and Psychology, and one is the benchmark theory (that is, Gambler's Ruin or Random Walk theory) specifically tailored to our case in the Entrepreneurship domain. We deliberately selected the two non-random theories of company growth because we want to test if, and to what extent these also apply to the Entrepreneurship field – as many authors do (e.g., Handrito et al., 2020;

Parnell et al., 2012) advocate. The benchmark theory (i.e., the Gambler's Ruin or Random Walk theory) is a theory specifically tailored to the Entrepreneurship domain arguing that company growth is a random walk, thus – by extension – that company predictions in the Entrepreneurship field reflect a utopian ambition.

Competitive strategy theory focuses on the firm, and motive disposition theory on the individual (cf. Davidsson et al., 2010). Competitive strategy theory stresses the importance of strategy-versus-environment fit (e.g., Cannella & Monroe, 1997), and motive disposition theory underscores the influence of the key motivation of the individual entrepreneur (e.g., McClelland, 1987a). After identifying the critical explanatory variables central to these theories and constructing the associated measures with our data, we produce ranked predictions as to the relative employment growth performance of approximately 300 Belgian entrepreneurs and their companies. That is, we develop two predictive rankings. Later in 2023, we will test the predictive accuracy of both rankings vis-à-vis one another, with Gamble Ruins and 'Gibrat (1931) theory's randomness as the null benchmark, by comparing the two predictive rankings with that on the basis of realized growth.

Here, we hit the devil of structural breaks. What is a good explanatory variable in one context, could be of weak significance in other circumstances. Or, in other words, a good explanation of the past is not necessarily applicable to today's world, let alone to the future. This, of course, complicates the development of our predictive design. After all, the latter would imply that we should select variables for their *predictive* and *not* for their *explanatory* (circumstantial) value. Given that our approach is – to the best of our knowledge – new in the Social Sciences, we are however limited in our theoretical reasoning to what extant knowledge has to offer, thus being forced to select theories and variables based on existing, mainly explanatory, studies. As a by-catch, therefore, another part of the added value of our study lies in testing the predictive value of a selection of explanatory variables derived from generic theories. Hopefully, this will result in a further assessment of their *predictive* power.

4.1. Competitive strategy theory

For illustrative purposes, we select as our steppingstone classic contingency theory, which advocates that, to be able to reach highest company performance, a firm's strategy should fit with this firm's environment. Contingency theory is probably one of the most influential perspectives in the Business and Management literature, arguing that the adaptive alignment, congruence, match or fit between internal features and external contexts is key to explain outstanding outcomes (Miles & Snow, 1978, 2003; Naman & Slevin, 1993; Parker & van Witteloostuijn, 2010). Accordingly, any misfit or deviation from the ideal type of fit between internal organizational features and external environmental characteristics will produce lower performance outcomes. Indeed, within Strategy as a discipline, a one-size-fits-all strategic advice is argued to be a dead end; the precise nature of any 'optimal' (performance-maximizing) strategy critically depends upon environmental circumstances.

In the Strategy field, the classic notion of contingency fit that specific internal features of an organization (particularly processes, structures or technologies) fit with specific external environmental conditions (e.g., complexity, dynamism or uncertainty) is enriched by adding attributes of strategy (Child, 1972; Miles & Snow, 1978; Porter, 1980). This gives the by now standard and decade-old hypothesis that a strategy can only succeed to achieve high firm performance *if* this specific strategy fits with specific environmental circumstances (e.g., Hrebiniak & Joyce, 1985). This idea stems from the criterion-specific contingency tradition (Venkatraman, 1989), where company performance is taken as the fit anchor. Our first predictive ranking is derived from this well-known strategy–environment contingency fit argument (Cannella & Monroe, 1997; Carpenter et al., 2004; Hiller & Hambrick, 2005), following from the argument that strategy–environment fit predicts higher job growth.

Prior studies in Strategy (e.g., Doty et al., 1993; Ketchen et al., 1993) have applied and expanded this strategy–environment fit concept to include a range of organizational aspects, identifying a wide variety of fit metrics, ranging from organizational characteristics and strategy (White, 1986) to governance structure and strategy (Yin & Zajac, 2004), business model and strategy (Zott & Amit, 2008), and more. We develop our theoretical argumentation on the back of this contingency fit theory, working with well-established insights from the strategy–environment fit literature. We start from the main and very well-established twofold conclusion of Strategy research regarding the strategy−environment fit relationship: (1) A cost leadership strategy is effective to achieve high firm performance in stable environments, and (2) a product/service differentiation strategy is the way to obtain high firm performance in dynamic environments.

In this study, to construct our predictive ranking, we primarily focus on the product/service differentiation strategy–environment fit relationship. The reason is twofold. One, a cost leadership strategy implies that a company is able to benefit from scale economies by producing large batches of end products or services, something smaller firms (which are our focus) are simply unable to reach. Two, additionally, according to the cost leadership argument, several sources of cost decline operate along the experience curve. If larger cumulative output causes a downward shift along the company's average cost curve, a competitive advantage can be attained (Amit, 1986). Cost declines can induce a movement *along* the average cost curve, or a movement *of* the average cost curve. The first is often referred to as the scale effect, and the second as the learning effect (Amit, 1986). A scale effect does not imply job creation, because then *more* items can be produced with *less* resources. A learning effect involves labor efficiencies, implying that *less* labor input is needed for the production of one unit. Given that the current paper focuses on the prediction of job *creation* of small firms, a focus on cost leadership is not appropriate.

Instead, product/service differentiation implies that customers 'give weight to product attributes other than price' (Murray, 1988, p. 394). In this case, job creation tends to be involved. Indeed, small firms often opt for niche differentiation strategies. To be able to excel, a company must find, build and sustain a competitive advantage through, e.g., its product offering, brand image, packaging, or sales services (Murray, 1988). For this, innovation is a driving force. Although innovation, technological change and entrepreneurial activities indeed are positively related to job creation (Wong et al., 2005), environmental factors such as demand attributes and wage increases undoubtedly impact this relationship (see Bogliacino & Pianta, 2010). We focus on the generic contingency theory concept of environmental dynamism. The latter is referred to as the 'Schumpeter mark I effect: The net entry of firms in industries suggests the presence of technological opportunities exploited by innovative firms that are able to *create* new jobs' (Bogliacino & Pianta, 2010, p. 804). Thus, environmental changes and shifting opportunities allow for product/service differentiation by (often small) innovative firms. Indeed, contingency theory argues that companies that succeed to adopt a product/service differentiation strategy aiming at constantly adapting to such a dynamic environment (Bourgeois & Eisenhardt, 1988; Miller, 1986, 1988), are able to achieve the highest company performance, implying job growth.

Prediction 1. : Companies opting for a product / service differentiation strategy while operating in a dynamic environment will be characterized by high future employment growth.

4.2. Motive disposition theory

For decades, theories within Business and Management are enriched with insights from neighboring behavioral disciplines such as Cognitive Science and Personality Psychology (Boone et al., 1996; Cannella & Monroe, 1997; Carpenter et al., 2004; Powell et al., 2011). Highly relevant in this context is motive disposition theory (MDT: McClelland

1987a, b). MDT uses the concept of human needs, relying on the basic premise that the understanding of psychological needs is essential for understanding human functioning, such as motivation, behavior, and goal pursuit (McClelland et al., 1989; Schultheiss & Brunstein, 2010a). Motives are defined as the capacity to experience a specific type of incentive as pleasurable, and relates to the extent that people can derive satisfaction from these incentives (Stanton et al., 2010). Motives involve stable differences in affective reactions to different classes of incentives, goals and desires that drive individual behavior (McClelland et al., 1953; Stanton et al., 2010).

MDT recognizes that behavior may be driven by many needs (Murray, 1943; Schultheiss et al., 2010), but reconciles on the idea that most of human behavior can be explained by three basic psychological needs: Need for power, need for achievement, and need for affiliation. Need for achievement relates to the dispositional concern for doing well according to a standard of excellence. People high in need for achievement aim for high task performance and strive for efficiency in task accomplishment (McClelland et al., 1953; Schultheiss & Brunstein, 2010a). Affiliation-motivated people get satisfaction out of building, maintaining and restoring positive social relationships with others. They aim to feel socially related, and they want to experience reciprocal care and warmth with others (Heyns et al., 1958; Schultheiss & Brunstein, 2010a). Need for power describes the need to have social, physical or emotional impact. Power-motivated people aim for prestige and reputation, and they like to be seen and love to control others (Schultheiss & Brunstein, 2010b; Winter, 1973).

MDT does distinguish implicit from explicit motives (McClelland et al., 1989). Explicit motives represent a part of people's self-concept and include an individual's conscious reflections about her or his needs, cognitive beliefs, and rational choices of what is important to strive for in one's life (Schultheiss et al., 2009; Spangler, 1992). In contrast, implicit motives represent an individual's idealized self-concept and operate outside a person's awareness (Winter et al., 1998). Implicit motives are not accessible for conscious reflections, or at least much less so. The automaticity feature of implicit motives means that stimuli in the environment may automatically activate implicit motives, and hence instigate behavioral processes without conscious reflections (McClelland et al., 1989; Stanton et al., 2010).

Implicit and explicit motives predict different types of behavior. Implicit motives are associated with spontaneous behavior and behavioral trends over time, whereas explicit motives rather relate to the immediate outcomes of specific situations that are often based on cognitive reflections and decisions (Friese et al., 2009; Stoeckart et al., 2016; Thrash & Elliot, 2002; Woike et al., 2003). Therefore, because we predict long-term success in the current study, we expect that implicit rather than explicit motives will predict employment growth. Entrepreneurship research has long debated if and to what extent the motives of entrepreneurs explain the performance of their companies (e.g., Brandstätter, 2011; Carsrud & Brännback, 2011; Hisrich et al., 2007; McClelland, 1987a; Stewart & Roth, 2007; Yan et al., 2007). Many conclude that an innate need for achievement is essential to become a successful entrepreneur (e.g., Collins et al., 2004; McClelland, 1987a; Sagie & Elizur, 1999). Interestingly, the achievement motive is mostly linked to entrepreneurial intent and the establishment of a new venture, but not so much with company growth in general and employment growth in particular (e.g., Collins et al., 2004; McClelland, 1987; Sagie & Elizur, 1999). Hence, we do not expect a relationship between need for achievement and employment growth.

Consensus about the affiliation and power motives has not been reached. On the one hand, research suggests that successful entrepreneurship not only requires high need for achievement, but also low need for power (Winter, 2010). Yet, on the other hand, other studies advocate that high need for power is paramount to successful entrepreneurship. Getting things done through other people, influencing others, having impact on the world and other typical need for power attributes are all ascribed to key characteristics of successful entrepreneurs (Chell et al., 2016; de Vries, 1985; Furnham et al., 2009; Hisrich, 1990; Langan-Fox & Roth, 1995).

A plausible reason as to why consensus regarding the motive profile of a successful entrepreneur is missing, may be the diversity in business performance or entrepreneurial success metrics (Bygrave & Hofer, 1992; Davidsson, 2016). Business growth is perhaps the most prominent way to define entrepreneurial success (Davidsson et al., 2009). Yet, growth can take many shapes, such as growth in sales, employment, profit and/or assets (Davidsson, 2016), which are likely to be associated with different drivers and consequences (Davidsson, 2016; Shepherd & Wiklund, 2009). Given the different forms success can take, different types of motives may underlie different facets of business success. As we focus on job creation, we expect that need for affiliation is positively and need for power is negatively related to SME employment growth.

More specifically, need for affiliation drives individuals toward collective interests (Baumeister & Leary, 1995; Leary et al., 2013; Pillow et al., 2015) and increases individuals' willingness to help group members (Den Hartog et al., 2007). Tiessen (1997), for example, showed that collectivistic/affiliation-oriented entrepreneurs prefer to strengthen the 'in-group' ties by building close relational links in tandem with investments in the company, rather than investing resources in new venture formation and making major innovations. Need for affiliation was also found to be the major motive for entrepreneurs to contribute to the welfare of the community by creating a company that provides jobs and social welfare (Barba-Sanchez & Atienza-Sahuquillo, 2011). In a similar vein, Cornelius and Lane (1984) and Kirkpatrick et al. (2002) report a positive relationship of the affiliation motive with job creation in services organizations.

We expect the opposite for power-motivated entrepreneurs. As they excel in getting things done through other people (e.g., Fodor & Farrow, 1979; Fodor & Smith, 1982), they should be able to motivate their employees to give the best of themselves, not to obtain personal gains, but for the benefit of the company. In addition, power-motivated people like to take high risks (McClelland & Watson, 1973). This should translate in a relatively high number of risky business decisions such as a rapidly increasing degree of internationalization or a high number of business acquisitions (Kirkpatrick et al., 2002; Slabbinck et al., 2018).

Prediction 2. Companies that are led by entrepreneurs with high implicit affiliation motives and low implicit power motives will be characterized by high future employment growth.

5. Comparative predictive design

5.1. Sample and measures

Between October 2016 and October 2018, we gathered data from 294 Belgian entrepreneurs, their companies and their environments. For this, we worked with three data-gathering online tools: Two online questionnaires and one implicit association test. For further detail, we refer to van Witteloostuijn et al. (2020). The first questionnaire focuses on the company and environment. For example, we ask the entrepreneur which strategy (s)he adopts, and whether market turbulence is high. The second questionnaire consists of questions about the entrepreneur's personal attributes, such as motives and personality. The second survey includes a measure of McClelland's (1987) explicit motives. The online association test is a Brief Implicit Association Test (BIAT), used to measure implicit motives.

Product/service differentiation is measured through Treacy and Wiersema's (1993, 1995) product leadership value strategy position. We adopted the scale used by Reimann et al. (2010), which is an instrument originally developed and validated by Chaudhuri and Holbrook (2001), Kotha and Vadlamani (1995), Nayyar (1993), and Wirtz et al. (2007). We used six items with a five-point Likert scale ranging from 1 (totally disagree) to 5 (completely agree). Example questions are: 'We continuously refine and improve existing products or services', and 'The design

and functionality of our products or services is crucial to our competitive positioning'. The Cronbach alpha is good (α = 0.80).

Market turbulence is measured through Jaworski and Kohli's (1993) task environment scale. In a dynamic environment, product designs, distribution and delivery systems, and modes of production have to anticipate changing customer demand, technological advancement and/or market competition, calling for a product/service differentiation approach. In this paper, we focus on market turbulence as a measure of fast-changing customer needs. Respondents were asked to answer six statements on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). The items examine whether and to what extent customer preferences change over time. Confirmatory factor analyses revealed that three items needed to be deleted, giving a market turbulence variable with the following three items: 'In our kind of business, customers' product or service preferences change quite a bit over time', 'Sometimes our customers are very price-sensitive, but on other occasions, price is relatively unimportant', and 'Our customers tend to look for new products or services all the time'. The Cronbach alpha is satisfactory (α = 0.66).

We measured *explicit motives* with the power and affiliation subscales of the Personality Research Form (PRF: Jackson, 1984), which is a self-report inventory of motivational motives. Participants were asked to what extent each statement fitted them. Sample items of the subscales are: 'The ability to be a leader is very important to me' (power subscale) and 'I truly enjoy myself at social gatherings' (affiliation subscale). Each subscale consists of eleven seven-point Likert-type items with anchors 1 = 'Fits not at all' and 7 = 'Fits very well'. Confirmatory factor analysis indicated that the factor loading of one item from the affiliation subscale was too low. This item was deleted. We calculated the individual measures as the mean score of the scale items. High scores indicate a good fit between the trait and the participants. The Cronbach alphas are good (Power α = .75; Affiliation α = 0.84).

Because *implicit motives* operate outside a person's awareness and (most) people lack introspective access to their implicit system (Pang, 2010; Schultheiss & Pang, 2007; Slabbinck et al., 2011), implicit motives cannot be assessed with direct, self-reported measures, but have to be captured through indirect measures. We applied the Brief Implicit Association Test (BIAT), which is a shortened and simplified version of the Implicit Association Test (IAT: Greenwald et al., 1998). The BIAT is a computerized response latency task designed to measure the relative strength of associations between two contrasted concepts (e.g., 'sunshine – pleasant' versus 'sunshine – unpleasant'). In brief, if people are faster to categorize, for example, stimuli that are related to 'sunshine' to situations in which 'sunshine' is visually paired with 'pleasant' on a computer screen than to situations in which 'sunshine' is visually paired with 'unpleasant', people are assumed to have a positive implicit attitude toward sunshine. Sriram and Greenwald (2009) and Slabbinck et al. (2018) provide excellent and detailed descriptions of the BIAT procedure. In the current study, we assessed implicit affiliation and power motives by means of the BIAT method, adopting the procedure of Slabbinck et al. (2018). Following Nosek et al. (2014), we used data from both practice and critical blocks to compute BIAT scores. We recoded extreme latencies below 400 ms and above 10,000 ms to these boundaries, and we discarded the first four trials of each block. We calculated individual BIAT scores using the D score (Greenwald et al., 2003). D scores range between −2 and 2: The higher the score, the higher the individual's implicit power and affiliation motive.

5.2. Predictive rankings

We first calculate the mean scores of all items of a construct. Because implicit and explicit motives were measured on different scales, we rescaled these measures in such a way that the lowest scores on each measure equal 1 and the highest score is 10. We do this to give each construct an equal weight in the calculation of the predictive scores. Moreover, omitting negative scores facilitates the interpretation of multiplications that involves (multiple) negative scores. Rescaling of the market turbulence and product/service differentiation measures was not needed because both scales were assessed on five-point Likert scales.

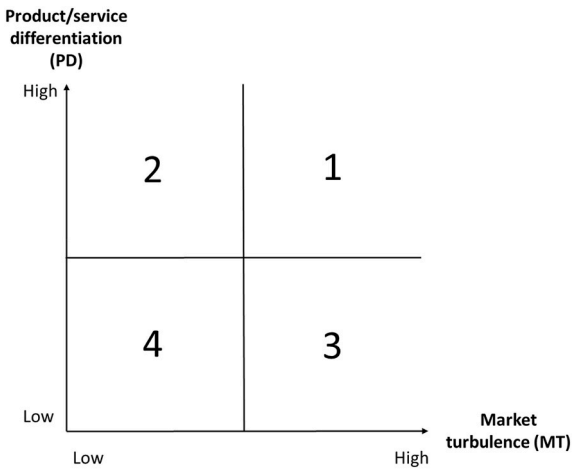

Fig. 1. Visualization of *Prediction 1*.

Table 1
Spearman's rho correlations of the predictive rankings.

	1.	2.	3.
1. Competitive strategy theory (*Prediction 1*)	–		
2. Implicit motives (*Prediction 2*)	0.059 (0.32)	–	
3. Explicit motives	−0.033 (0.57)	0.12 (0.048)	–

p-values between brackets; $n = 294$.

For the first prediction, a low score on product/service differentiation means that the SME does not adopt a product/service differentiation strategy (hereafter called PD), and vice versa. A low score on market turbulence (hereafter called MT) implies that the SME operates in a stable environment, and vice versa. We first calculate the median of PD to find our anchor point. Then, we make two groups: One PD group with scores above the median, and one with scores below the median. Within each group, we calculate the median on MT. Using this median, we thus form two groups within each PD group. This results in four sub-groups: A 'high PD – high MT' group (= group 1), a 'high PD – low MT' group (= group 2), a 'low PD – low MT' group (= group 3), and a 'low PD – high MT' group (= group 4) (see Fig. 1).

For the first ranking, we subtract the two scores within each group and take their absolute value. For each group, we rank these difference scores from low to high, implying that low scores indicate that these SMEs are predicted to have a higher likelihood to perform better than other SMEs within their group with high difference scores. We then integrate all rankings in the following order: Group 1, Group 2, Group 3, and Group 4. Based on *Prediction 1*, we argue that SMEs in Group 1 are able to attain the highest performance in job creation. We expect that SMEs in Group 2 have higher job growth than those opting for low PD, but that given the mismatch with the environment, their performance is lower than the SMEs in Group 1. SMEs in Group 3 and Group 4 pursue a cost leadership strategy, implying that job growth is unlikely to be high. Given the mismatch with a highly turbulent market, we expect performance of SMEs in group 4 to be the lowest.

For the second prediction, we first reversed the rescaled need for power score so that high scores are associated with a low need for power. We then multiplied the reversed need for power scores with the implicit affiliation score. With reference to *Prediction 2*, high scores indicate that we expect that these SMEs have a higher likelihood to create additional jobs vis-à-vis SMEs with low scores. Additionally, we constructed a similar ranking on the basis of explicit motives, to provide evidence that explicit and implicit motives are indeed differently related to (predicted)

Table 2
Firm size descriptives.

	Prediction 1						Prediction 2						Prediction 3					
	Top 10%		44–55%		Bottom 10%		Top 10%		44–55%		Bottom 10%		Top 10%		44–55%		Bottom 10%	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Firm Size																		
1 to 4	19	55.9%	18	50.0%	21	56.8%	10	45.5%	11	45.8%	13	48.1%	13	48.1%	24	55.8%	12	38.7%
4 to 9	10	29.4%	13	36.1%	6	16.2%	7	31.8%	8	33.3%	9	33.3%	9	33.3%	9	20.9%	10	32.3%
9 to 19	3	8.8%	3	8.3%	7	18.9%	3	13.6%	5	20.8%	3	11.1%	3	11.1%	9	20.9%	6	19.4%
20 to 49	2	5.9%	0	0.0%	1	2.7%	2	9.1%	0	0.0%	1	3.7%	1	3.7%	0	0.0%	2	6.5%
50 to 99	0	0.0%	1	2.8%	2	5.4%	0	0.0%	0	0.0%	0	0.0%	1	3.7%	1	2.3%	0	0.0%
100 to 199	0	0.0%	1	2.8%	0	0.0%	0	0.0%	0	0.0%	1	3.7%	0	0.0%	0	0.0%	1	3.2%
200 to 499	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
500 to 999	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
>1000	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Total	34	100.0%	36	100.0%	37	100.0%	22	100.0%	24	100.0%	27	100.0%	27	100.0%	43	100.0%	31	100.0%

Table 3
Product/service orientation descriptives.

	Prediction 1						Prediction 2						Prediction 3					
	Top 10%		44–55%		Bottom 10%		Top 10%		44–55%		Bottom 10%		Top 10%		44–55%		Bottom 10%	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Product/Service Oriented																		
Product	3	8.3%	6	14.0%	6	11.3%	1	3.4%	4	12.5%	4	12.9%	2	5.7%	4	7.4%	3	8.3%
Mostly Product	12	33.3%	7	16.3%	10	18.9%	6	20.7%	5	15.6%	6	19.4%	10	28.6%	10	18.5%	8	22.2%
Both	16	44.4%	10	23.3%	19	35.8%	16	55.2%	10	31.3%	11	35.5%	11	31.4%	22	40.7%	11	30.6%
Mostly Service	4	11.1%	4	9.3%	7	13.2%	3	10.3%	7	21.9%	2	6.5%	7	20.0%	5	9.3%	3	8.3%
Service	1	2.8%	16	37.2%	11	20.8%	3	10.3%	6	18.8%	8	25.8%	5	14.3%	13	24.1%	11	30.6%
Total	36	100.0%	43	100.0%	53	100.0%	29	100.0%	32	100.0%	31	100.0%	35	100.0%	54	100.0%	36	100.0%

Table 4
Firm age descriptives.

	Prediction 1			Prediction 2			Prediction 3		
	Top 10%	44–55%	Bottom 10%	Top 10%	44–55%	Bottom 10%	Top 10%	44–55%	Bottom 10%
Firm Age	15.28	15.6	18.66	14.17	14.83	17.07	16	12.83	16.21

job growth, with the latter a more important predictor of job growth than the former. Table 1 shows the Spearman's rho correlations between the predictive rankings. The Spearman's rho correlations show that the predicted rankings are not or only weakly correlated. This indicates that different theories yield different competing predictions regarding future employment growth.

In Tables 2–4, we provide an overview of the 10 percent highest ranked SMEs, those in the range from 45 to 55 percent, and the 10 percent lowest ranked SMEs of our pair of rankings, as well as that on the basis of explicit motives. Full details of all SMEs rankings are available on the Open Science Framework (10.17605/OSF.IO/G2PRN). We provide basic company demographics for these SMEs, capturing traditional control variables, being employment size (in fte), age, and whether the SME is service/product-oriented. Firm size is measured as an ordinal variable, containing the following categories: '1–4', '4–9', '9–19', '20–49', '50–99', '100–199', and '>199' employees. Please note that, in line with our paper's SME focus, none of our companies has more than 200 employees. Firm age is measured as a continuous variable. Product/service orientation is a nominal variable, with the following categories: 'Product-oriented', 'mostly product-oriented, with a few supporting services', 'both product and service-oriented', 'mostly service-oriented, with a few supporting products', and 'service-oriented'.

From these tables, we observe that differences across the predicted performance categories per prediction are marginal, implying that this list of what would have been control variables in a traditional post-dictive explanatory analysis cannot explain predicted performance heterogeneity. For firm size, we execute a Kruskal-Wallis test to examine the differences on firm size according to the predicted performance group (top 10%, middle 44–45%, and bottom 10%). No significant differences were found for *Prediction 1* (Chi square = 0.19, p = .91, df = 2), or *Prediction 2* (Chi square = 0.08, p = .96, df = 2), nor the explicit motives prediction (Chi square = 1.91, p = .38, df = 2). For firm age, we executed ANOVAs, again without finding significant differences according to the predicted performance group (top 10%, middle 44–45%, and bottom 10%) (for *Prediction 1*: F = 0.73, sig. = 0.48; for *Prediction 2*: F = 0.41, sig. = 0.68; for the explicit motives prediction: F = 1.29, sig. = 0.28). Finally, for product/service orientation, we performed Chi Square tests to examine potential differences according to the predicted performance groups. No significant differences emerged for *Prediction 2* (Chi square = 9.44, p = .31, df = 8) or *Prediction 3* (Chi square = 6.63, p = .58, df = 8), but Prediction 3 revealed a significant difference in product/service orientation (Chi square = 17.47, p = .026, df = 8). Visual inspection of the Table 3 shows that, according to *Prediction 1*, product/service-oriented companies are less represented in the group of top-performing enterprises.

6. Looking forward

Our predictions will be submitted as appendices to this paper and will thus be stored at *Social Sciences and Humanities Open*. With performance data from 2021, we will compare our predictive rankings with the actual job growth performance of our 294 SMEs. By then, we can and will assess whether competitive strategy theory's *Prediction 1* outperforms motive disposition theory's *Prediction 2*, or vice versa, and how both fare vis-à-vis Gambler Ruin's and Random Walk theory's prediction of randomness. We will do so by applying both traditional research methods (e.g., comparing rankings by means of Spearmen correlation, the Wilcoxon ranked-sum test and/or the Jaccard similarity score) as well alternative research methods that are more appropriate to falsify findings and, hence, fit better with the Popperian idea (Tarantola, 2006) (e.g., Bayesian research methods such as the Bayesian signed-rank tests).

A final twofold remark relates to post hoc analyses regarding other SME performance metrics. We know from the Entrepreneurship literature that drivers of difference types of performance outcomes tend not to overlap completely (see, e.g., Davidsson et al., 2010). That is, what determines, say, profitability improvement or mere survival may deviate from what drives job creation. Also, different types of growth – e.g., in terms of employment vis-à-vis sales – may be associated with different underlying causal mechanisms. In the current study, we decided to focus on job growth, for reasons explained above. However, in post hoc analyses, we will run multivariate regression analyses to explore the extent to which and in what way the determinants across different SME performance metrics do differ. Those regarding mere survival serve another purpose – i.e., to explore to what extent our comparative predictive rankings analyses may suffer from survivor bias.

To conclude, in this paper, we develop and conduct a comparative predictive study that offers an alternative research design that adds to the Social Sciences community's methodology toolkit in three important ways: (1) Prediction contributes to the field's relevance; (2) assessment of the validity of explanatory variables in the context of prediction; and (3) explicit inter-theory testing, including a substantive null. We strongly believe that this is a design that is squarely in line with the Popperian Philosophy of Science, and much more so than the traditional explanation of the past through null hypothesis significance testing (cf. Starbuck, 2016; van Witteloostuijn, 2019, 2020). With our case in the Entrepreneurship field, and in the words of Anderson et al. (2020): "We believe that the next frontier in theory testing research involves improving our ability to make causal *predictions* about entrepreneurship phenomena" (italics added).

CRediT authorship contribution statement

Arjen van Witteloostuijn: Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Funding acquisition. **Johanna Vanderstraeten:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Hendrik Slabbinck:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Marcus Dejardin:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Julie Hermans:** Writing – review & editing. **Wim Coreynen:** Investigation, Resources, Data curation, Project administration.

Declaration of competing interest

None.

References

Amit, R. (1986). Cost leadership strategy and experience curves. *Strategic Management Journal, 7*(3), 281–292.

Amrhein, V., Greenland, S., & McShane, B. (2019). Scientists rise up against statistical significance. more than 800 signatories *Nature, S67*, 307.

Anderson, B. S., Wennberg, K., & McMullen, J. S. (2020). Editorial: Enhancing quantitative theory-testing entrepreneurship research. *Journal of Business Venturing* (in press).

Andrews, I., & Kasy, M. (2019). Identification of and correction for publication bias. *The American Economic Review, 109*(8), 2766–2794.

Autio, E. (2007). *Global entrepreneurship monitor: 2007 global report on high-growth entrepreneurship*. Wellesley, MA/London: Babson College and London Business School.

Baker, M. (2016). Biotech giant publishes failures to confirm high-profile science. *Nature, 530*, 141. https://doi.org/10.1038/nature.2016.19269

Barba-Sanchez, V., & Atienza-Sahuquillo, C. (2011). Reasons to create a new venture: A determinant of entrepreneurial profiles. *African Journal of Business Management, 5*(28), 11497–11504.

Baumeister, R. F., & Leary, M. R. (1995). The Need to Belong: Desire for interpersonal attachments as a fundamental human emotion. *Psychological Bulletin, 117*(3), 497–529.

Beugelsdijk, S., van Witteloostuijn, A., & Meyer, K. E. (2020). The evolving rules of data management in the publication process: Enhancing data access and research transparency (DART). *Journal of International Business Studies, 51*, 887–905.

Birkinshaw, J., Healey, M. P., Suddaby, R., & Weber, K. (2014). Debating the future of management research. *Journal of Management Studies, 51*(1), 38–55.

Bogliacino, F., & Pianta, M. (2010). Innovation and employment: A reinvestigation using revised pavitt classes. *Research Policy, 39*(6), 799–809.

Boone, C., De Brabander, B., & van Witteloostuijn, A. (1996). CEO locus of control and small firm performance: An integrative framework and empirical test. *Journal of Management Studies, 33*(5), 667–700.

Bosma, B., & van Witteloostuijn, A. (2021). *Dichotomania versus the richness of being*. Mimeo. Amsterdam: Vrije Universiteit Amsterdam.

Bourgeois, L. J., & Eisenhardt, K. M. (1988). Strategic decision processes in silicon valley: Four cases in the microcomputer industry. *Management Science, 34*(7), 816–835.

Brandstätter, H. (2011). Personality aspects of entrepreneurship: A look at five meta-analyses. *Personality and Individual Differences, 51*(3), 222–230.

Brodeur, A., Lé, M., Sangnier, M., & Zylberberg, Y. (2015). Star Wars: The empirics strike back. *American Economic Journal: Applied Economics, 8*(1), 1–32.

Bygrave, W. D., & Hofer, C. W. (1992). Theorizing about entrepreneurship. *Entrepreneurship: Theory and Practice, 16*(2), 13–22.

Cannella, A. A., & Monroe, M. J. (1997). Contrasting Perspectives on Strategic Leaders: Toward a more realistic view of top managers. *Journal of Management, 23*(3), 213–237.

Carpenter, M. A., Geletkanycz, M. A., & Sanders, W. G. (2004). Upper Echelons Research Revisited: Antecedents, elements, and consequences of top management team composition. *Journal of Management, 30*(6), 749–778.

Carsrud, A. L., & Brännback, M. (2011). Entrepreneurial Motivations: What do we still need to know? *Journal of Small Business Management, 49*(1), 9–26.

Cassar, G. (2006). Entrepreneur opportunity costs and intended venture growth. *Journal of Business Venturing, 21*(5), 610–632.

Cassar, G. (2007). Money, money, money? A longitudinal investigation of entrepreneur career reasons, growth preferences and achieved growth. *Entrepreneurship & Regional Development, 19*(1), 89–107.

Castle, J. L., Fawcett, N. W., & Hendry, D. F. (2010). Forecasting with equilibrium-correction models during structural breaks. *Journal of Econometrics, 158*(1), 25–36.

Caves, R. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature, 36*(4), 1947–1982.

Chaudhuri, A., & Holbrook, M. B. (2001). The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. *Journal of Marketing, 65*(2), 81–93.

Chell, E., Spence, L. J., Perrini, F., & Harris, J. D. (2016). Social entrepreneurship and business ethics: Does social equal ethical? *Journal of Business Ethics, 133*(4), 619–625.

Child, J. (1972). Organizational structure, environment, and performance: The role of strategic choice. *Sociology, 6*(1), 1–22.

Coad, A., Daunfeldt, S. O., & Halvarsson, D. (2018). Bursting into Life: Firm growth and growth persistence by age. *Small Business Economics, 50*(1), 55–75.

Coad, A., Frankish, J. S., Roberts, R. G., et al. (2016). Predicting new venture survival and growth: Does the fog lift? *Small Business Economics, 47*(1), 217–241.

Coad, A., Frankish, J. S., Roberts, R. G., & Storey, D. J. (2013). Growth paths and survival chances: An application of Gambler's Ruin theory. *Journal of Business Venturing, 28*(5), 615–632.

Collins, C. J., Hanges, P. J., & Locke, E. A. (2004). The relationship of achievement motivation to entrepreneurial behavior: A meta-analysis. *Human Performance, 17*(1), 95–117.

Conradie, W., Palmigiano, A., Wijnberg, N., & van Witteloostuijn, A. (2019). *Organizing inter-theory competition: A formal logic analysis of theory fragmentation and database reuse*. Mimeo. Amsterdam: Vrije Universiteit Amsterdam.

Cornelius, E. T., & Lane, F. B. (1984). The power motive and managerial success in a professionally oriented service industry organization. *Journal of Applied Psychology, 69*(1), 32–39.

Davidsson, P. (2016). Entrepreneurship as a research domain. In P. Davidsson (Ed.), *33. Researching entrepreneurship: Conceptualization and design* (pp. 21–40). Switzerland: Springer International Publishing. International Studies in Entrepreneurship book series.

Davidsson, P., Achtenhagen, L., & Naldi, L. (2010). Small firm growth. *Foundations and Trends in Entrepreneurship, 6*(2), 69–166.

Davidsson, P., Steffens, P., & Fitzsimmons, J. (2009). Growing profitable or growing from profits: Putting the horse in front of the cart? *Journal of Business Venturing, 24*(4), 388–406.

Den Hartog, D. N., De Hoogh, A. H. B., & Keegan, A. E. (2007). The interactive effects of belongingness and charisma on helping and compliance. *Journal of Applied Psychology, 92*(4), 1131–1139.

Derbyshire, J., & Garnsey, E. (2014). Firm growth and the illusion of randomness. *Journal of Business Venturing Insights, 1*(2), 8–11.

Doty, D. H., Glick, W. H., & Huber, G. P. (1993). Fit, equifinality and organizational effectiveness: A test of two configurational theories. *Academy of Management Journal, 36*(6), 1196–1250.

Edelman, L. F., Brush, C. G., Manolova, T. S., & Greene, P. G. (2010). Start-up motivations and growth intentions of minority nascent entrepreneurs. *Journal of Small Business Management, 48*(2), 174–196.

Fanelli, D. (2018). Opinion: Is science really facing a reproducibility crisis, and do we need it to? *Proceedings of the National Academy of Sciences, 115*(11), 2628–2631.

Fodor, E. M., & Farrow, D. L. (1979). The power motive as an influence on use of power. *Journal of Personality and Social Psychology, 37*(11), 2091–2097.

Fodor, E. M., & Smith, T. (1982). The power motive as an influence on group decision making. *Journal of Personality and Social Psychology, 42*(1), 178–185.

Friese, M., Hofmann, W., & Schmitt, M. (2009). When and why do implicit measures predict behaviour? Empirical evidence for the moderating role of opportunity, motivation, and process reliance. *European Review of Social Psychology, 19*(1), 285–338.

Furnham, A., Eracleous, A., & Chamorro-Premuzic, T. (2009). Personality, motivation and job satisfaction: Hertzberg meets the big five. *Journal of Managerial Psychology, 24*(8), 765–779.

Gibrat, R. (1931). *Les inégalités économiques*. Paris: Librairie du Recueil Sirey.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology, 74*(6), 1464–1480.

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology, 85*(2), 197–216.

Gulati, R. (2007). Tent Poles, Tribalism, and Boundary Spanning: The rigor-relevance debate in management research. *Academy of Management Journal, 50*(4), 775–782.

Handrito, R. P., Slabbinck, H., & Vanderstraeten, J. (2020). *Enjoying or refraining from risk? The impact of implicit need for achievement and risk perception on SME internationalization*. Cross Cultural and Strategic Management. https://doi.org/10.1108/CCSM-03-2019-0068 (in press).

Hermans, J., Vanderstraeten, J., van Witteloostuijn, A., Dejardin, M., Ramdani, D., & Stam, E. (2015). Ambitious entrepreneurship: A review of growth aspirations, intentions, and expectations. *Advances in Entrepreneurship, Firm Emergence and Growth, 17*, 127–161.

Heyns, R. W., Veroff, J., & Atkinson, J. (1958). A scoring manual for the affiliation motive. In J. Atkinson (Ed.), *Motives in fantasy, action and society* (pp. 205–218). Princeton, NJ: Van Nostrand.

Hiller, N. J., & Hambrick, D. C. (2005). Conceptualizing Executive Hubris: The role of (hyper–) core self–evaluations in strategic decision–making. *Strategic Management Journal, 26*(4), 297–319.

Hisrich, R. D. (1990). Entrepreneurship/intrapreneurship. *American Psychologist, 45*(2), 209–222.

Hisrich, R. D., Langan-Fox, J., & Grant, S. (2007). Entrepreneurship research and practice: A call to action for psychology. *American Psychologist, 62*(6), 575–589.

Hofman, J. M., Sharma, A., & Watts, D. J. (2017). Prediction and explanation in social systems. *Science, 355*(6324), 486–488.

Hrebiniak, L. G., & Joyce, W. F. (1985). Organizational Adaptation: Strategic choice and environmental determinism. *Administrative Science Quarterly, 30*(3), 336–349.

Ioannidis, J. P. (2005). Why most published research findings are false. *PLoS Medicine, 2*(8), e124.

Ioannidis, J. P. (2008). Why most discovered true associations are inflated. *Epidemiology, 19*(5), 640–648.

Jackson, D. (1984). *Personality research form (3rd ed.). Port huron: Sigma assessment systems*.

Jaworski, B. J., & Kohli, A. J. (1993). Market orientation: Antecedents and consequences. *Journal of Marketing, 57*(3), 53–70.

Ketchen, D. J. J., Thomas, J. B., & Snow, C. C. (1993). Organizational configurations and performance: A comparison of theoretical approaches. *Academy of Management Journal, 36*(6), 1278–1313.

Kirkpatrick, S. A., Wofford, J. C., & Baum, J. R. (2002). Measuring motive imagery contained in the vision statement. *The Leadership Quarterly, 13*(2), 139–150.

Kolkman, D., Lee, G., & van Witteloostuijn, A. (2019). *Data science and automation in the process of theorizing: Machine learning's power of abduction*. Mimeo. Amsterdam: Vrije Universiteit Amsterdam.

Kolkman, D., & van Witteloostuijn, A. (2019). *Data science in strategy: Machine learning and text analysis in the study of firm growth, tinbergen institute discussion paper 2019-066/VI*. Amsterdam/Rotterdam: Tinbergen Institute.

Kotha, S., & Vadlamani, B. L. (1995). Assessing Generic Strategies: An empirical investigation of two competing typologies in discrete manufacturing industries. *Strategic Management Journal, 16*(1), 75–83.

Langan-Fox, J., & Roth, S. (1995). Achievement motivation and female entrepreneurs. *Journal of Occupational and Organizational Psychology, 68*(3), 209–218.

Leary, M. R., Kelly, K. M., Cottrell, C. A., & Schreindorfer, L. S. (2013). Construct validity of the need to belong scale: Mapping the nomological network. *Journal of Personality Assessment, 95*(6), 610–625.

McClelland, D. C. (1987a). Characteristics of successful entrepreneurs. *Journal of Creative Behavior, 21*(3), 219–233.

McClelland, D. C. (1987b). *Human motivation*. Cambridge: CUP Archive.

McClelland, D. C., Atkinson, J., Clark, R. A., & Lowell, E. L. (1953). *The achievment motive*. East Norwal, CT: Appleton-Century-Crofts.

McClelland, D. C., Koestner, R., & Weinberger, J. (1989). How do self-attributed and implicit motives differ? *Psychological Review, 96*(4), 690–702.

McClelland, D. C., & Watson, R. I. (1973). Power motivation and risk-taking behavior. *Journal of Personality, 41*(1), 121–139.
Meyer, K. E., van Witteloostuijn, A., & Beugelsdijk, S. (2017). What's in a p? Reassessing best practices for conducting and reporting hypothesis-testing research. *Journal of International Business Studies, 48*(5), 535–551.
Miles, R. E., & Snow, C. C. (1978). *Organizational strategy, structure, and process*. New York, NY: McGraw Hill. (reprinted as Miles, R. E., & Snow, C. C. (2003). Organizational Strategy, Structure, and Process. Stanford, CA: Stanford Business Classics).
Miller, D. (1986). Configurations of strategy and structure: Towards a synthesis. *Strategic Management Journal, 7*(3), 233–249.
Miller, D. (1988). Relating porter's business strategies to environment and structure: Analysis and performance implications. *Academy of Management Journal, 31*(2), 280–308.
Murray, H. A. (1943). *Thematic apperception test*. Cambridge: Harvard University Press.
Murray, A. I. (1988). A contingency view of porter's 'generic strategies. *Academy of Management Review, 13*(3), 390–400.
Naman, J. L., & Slevin, D. P. (1993). Entrepreneurship and the concept of fit: A model and empirical tests. *Strategic Management Journal, 14*(2), 137–153.
Nayyar, P. R. (1993). On the measurement of competitive strategy: Evidence from a large multiproduct U.S. Firm. *Academy of Management Journal, 36*(6), 1652–1669.
Nosek, B., Bar-Anan, Y., Sriram, N., & Greenwald, A. (2014). Understanding and using the brief implicit association test. *PLoS One, 9*(12), Article e110938.
Pang, J. S. (2010). Content coding methods in implicit motive assessment: Standards of measurement and best practices for the picture story exercise. In O. C. Schultheiss, & J. Brunstein (Eds.), *Implicit motives* (pp. 119–150). New York: Oxford University Press.
Parker, S. C. (2018). *The economics of entrepreneurship*. Cambridge: Cambridge University Press.
Parker, S. C., & van Witteloostuijn, A. (2010). A general framework for multidimensional contingency fit. *Organization Science, 21*, 540–553.
Parnell, J. A., Lester, D. L., Long, Z., & Köseoglu, M. A. (2012). How environmental uncertainty affects the link between business strategy and performance in SMEs: Evidence from China, Turkey, and the USA. *Management Decision, 50*(4), 546–568.
Pesaran, M. H., Pettenuzzo, D., & Timmermann, A. (2006). Forecasting time series subject to multiple structural breaks. *The Review of Economic Studies, 73*(4), 1057–1084.
Pillow, D. R., Malone, G. P., & Hale, W. J. (2015). The need to belong and its association with fully satisfying relationships: A tale of two measures. *Personality and Individual Differences, 74*, 259–264.
Popper, K. R. (1945a). *Open society and its enemies: Plato*. London: Routledge & Kegan Paul.
Popper, K. R. (1945b). *Open society and its enemies: Hegel and marx*. London: Routledge & Kegan Paul.
Porter, M. E. (1980). *Competitive strategy*. New York, NY: Free Press.
Powell, T. C., Lovallo, D., & Fox, C. R. (2011). Behavioral strategy. *Strategic Management Journal, 32*(13), 1369–1386.
van Praag, M., van Witteloostuijn, A., & van der Sluis, J. (2013). The higher returns to formal education for entrepreneurs versus employees. *Small Business Economics, 40*(2), 375–396.
Reimann, M., Schilke, O., & Thomas, J. S. (2010). Toward an Understanding of Industry Commoditization: Its nature and role in evolving market competition. *International Journal of Research in Marketing, 27*(2), 188–197.
Sagie, A., & Elizur, D. (1999). Achievement motive and entrepreneurial orientation: A structural analysis. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 20*(3), 375–387.
Schultheiss, O. C., & Brunstein, J. C. (2010a). *Implicit motives*. New York: Oxford University Press.
Schultheiss, O. C., & Brunstein, J. C. (Eds.). (2010b). *Implicit motives*. New York: Oxford University Press.
Schultheiss, O. C., & Pang, J. S. (2007). Measuring implicit motives. In R. W. Robins, R. C. Fraley, & R. Krueger (Eds.), *Handbook of research methods in personality Psychology* (pp. 322–344). New York: Guilford Press.
Schultheiss, O. C., Rösch, A. G., Rawolle, M., Kordik, A., & Graham, S. (2010). Implicit Motives: Current topics and future directions. In T. C. Urban, & S. A. Karabenick (Eds.), *The decade ahead: Theoretical perspectives on motivation and achievement* (pp. 199–233). Bingly: Emerald Group Publishing Limited.
Schultheiss, O. C., Yankova, D., Dirlikov, B., & Schad, D. J. (2009). Are implicit and explicit motive measures statistically independent? A fair and balanced test using the picture story exercise and a cue- and response-matched questionnaire measure. *Journal of Personality Assessment, 91*(1), 72–81.
Shane, S. (2008). *The illusions of entrepreneurship*. New Haven: Yale University Press.
Shepherd, D., & Wiklund, J. (2009). Are we comparing apples with apples or apples with oranges? Appropriateness of knowledge accumulation across growth studies. *Entrepreneurship: Theory and Practice, 33*(1), 105–123.
Shmueli, G. (2010). To explain or to predict? *Statistical Science, 25*(3), 289–310.
Slabbinck, H., De Houwer, J., & Van Kenhove, P. (2011). A pictorial attitude IAT as a measure of implicit motives. *European Journal of Personality, 25*(1), 76–86.
Slabbinck, H., van Witteloostuijn, A., Hermans, J., Vanderstraeten, J., Dejardin, M., Brassey, J., & Ramdani, D. (2018). The added value of implicit motives for management research: Development and first validation of a brief implicit association test (BIAT) for the measurement of implicit motives. *PLoS One, 13*(6), Article e0198094.
Spangler, W. (1992). Validity of questionnaire and TAT measures of need for achievement: Two meta-analyses. *Psychological Bulletin, 112*(1), 140–154.
Sriram, N., & Greenwald, A. G. (2009). The brief implicit association test. *Experimental Psychology, 56*(4), 283–294.
Stanton, S. J., Hall, J., & Schultheiss, O. C. (2010). Properties of motive-specific incentives. In O. C. Schultheiss, & J. C. Brunstein (Eds.), *Implicit motives* (pp. 245–278). New York, NY: Oxford University Press.
Starbuck, W. H. (2016). 60th Anniversary Essay: How journals could improve research practices in social science. *Administrative Science Quarterly, 61*(2), 165–183.
Stewart, W. H., & Roth, P. L. (2007). A meta-analysis of achievement motivation differences between entrepreneurs and managers. *Journal of Small Business Management, 45*(4), 401–421.
Stoeckart, P. F., Strick, M., Bijleveld, E., & Aarts, H. (2016). The implicit power motive predicts action selection. *Psychological Research, 81*(3), 560–570.
Sutton, J. (1997). Gibrat's legacy. *Journal of Economic Literature, 35*(1), 40–59.
Tarantola, A. (2006). Popper, bayes and the inverse problem. *Nature Physics, 2*(8), 492.
Thrash, T. M., & Elliot, A. J. (2002). Implicit and self-attributed achievement motives: Concordance and predictive validity. *Journal of Personality, 70*(5), 729–755.
Tiessen, J. H. (1997). Individualism, collectivism, and entrepreneurship: A framework for international comparative research. *Journal of Business Venturing, 12*(5), 367–384.
Tourish, D. (2019). *The triumph of nonsense in management studies*. Academy of Management Learning and Education (in press).
Treacy, M., & Wiersema, F. (1993). Customer intimacy and other value disciplines. *Harvard Business Review, 71*(1), 84–93.
Treacy, M., & Wiersema, F. (1995). *The discipline of market leaders*. Reading, MA: Perseus.
Tsui, A. (2017). Everyone can make a difference; together we can move the mountain: Re-orienting business and management research. Available at: https://rrbm.network/everyone-can-make-a-difference-together-we-can-move-the-mountain-re-orienting-business-management-research-anne-tsui. (Accessed 9 December 2019).
Venkatraman, N. (1989). The concept of fit in strategy research: Toward verbal and statistical correspondence. *Academy of Management Review, 14*(3), 423–444.
de Vries, M. F. R. (1985). The dark side of entrepreneurship. *Harvard Business Review, 63*(6), 160–167.
Walker, R. M., Brewer, G. A., Lee, M. J., Petrovsky, N., & van Witteloostuijn, A. (2019). Best practice recommendations for replicating experiments in public administration. *Journal of Public Administration Research and Theory, 29*, 609–626.
Wasserstein, R. L., & Lazar, N. A. (2016). The ASA's Statement on p-Values: Context, process, and purpose. *The American Statistician, 70*(2), 129–133.
Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a world beyond "$p < 0.05$". *The American Statistician, 73*(sup1), 1–19.
Watts, D. (2017). Should social science Be more solution-oriented? *Nature Human Behaviour, 1*. https://doi.org/10.1038/s41562-016-0015, 0015.
White, R. E. (1986). Generic business strategies, organizational context and performance: An empirical investigation. *Strategic Management Journal, 7*(3), 217–231.
Winter, D. G. (1973). *The power motive*. New York: Free Press.
Winter, D. G. (2010). Why achievement motivation predicts success in business but failure in politics: The importance of personal control. *Journal of Personality, 78*(6), 1637–1667.
Winter, D. G., John, O. P., Stewart, A. J., Klohnen, E. C., & Duncan, L. E. (1998). Traits and Motives: Toward an integration of two traditions in personality research. *Psychological Review, 105*(2), 230–250.
Wirtz, B. W., Mathieu, A., & Schilke, O. (2007). Strategy in high-velocity environments. *Long Range Planning, 40*(3), 295–313.
van Witteloostuijn, A. (2016). What happened to popperian falsification? Publishing neutral and negative findings: Moving away from biased publication practices. *Cross-Cultural and Strategic Management, 23*, 481–508.
van Witteloostuijn, A. (2019). *A Revealing Journey through the Editorial Jungle: Why we should abandon null hypothesis statistical testing altogether*. Mimeo. Amsterdam: Vrije Universiteit Amsterdam.
van Witteloostuijn, A. (2020). New-day statistical thinking: A bold proposal for a radical change in practices. *Journal of International Business, 51*, 274–278.
van Witteloostuijn, A., Cannaerts, N., Coreynen, W., el Hejazi, van Hugten, J., … Vanderstraeten, J. (2020). Co-creative action research experiments—A careful method for causal inference and societal impact. *Social Sciences, 9*(10), 171. https://doi.org/10.3390/socsci9100171
van Witteloostuijn, A., & Kolkman, D. (2018). Is firm growth random? A machine learning perspective. *Journal of Business Venturing Insights, 10*, Article e00107.
Woike, B. A., Mcleod, S., & Goggin, M. (2003). Implicit and explicit motives influence accessibility to different autobiographical knowledge. *Personality and Social Psychology Bulletin, 29*(8), 1046–1055.
Wong, P. K., Ho, Y. P., & Autio, E. (2005). Entrepreneurship, innovation and economic growth: Evidence from GEM data. *Small Business Economics, 24*(3), 335–350.
Yan, L., Hao, Z., & Baron, R. A. (2007). Influence of founder CEOs' personal values on firm performance: Moderating effects of firm age and size. *Journal of Management, 33*(5), 673–696.
Yin, X., & Zajac, E. J. (2004). The strategy/governance structure fit relationship: Theory and evidence in franchising arrangements. *Strategic Management Journal, 25*(4), 365–383.
Zott, C., & Amit, R. (2008). The fit between product market strategy and business model: Implications for firm performance. *Strategic Management Journal, 29*(1), 1–26.