Uncovering the role of product innovation in the relation between firm size and growth[☆]

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Abstract

Robust evidence of a negative relation between firm size and growth motivates widespread policy support to small firms. However, the determinants of such dependence are poorly understood. We investigate the role of product innovation as possible driving factor, using sales data for all firms in the pharmaceutical industry. We find that the small firm-growth premium arises only for firms switching products in their portfolio, and that such premium is driven by product innovation, either new-to-world, which leads to larger impact of new products, or new-to-firm, which mitigates cannibalization. We urge policy makers to prioritize innovation policies in supporting small firms.

Keywords: Gibrat law; firm growth; small firms; product innovation; product switching.

1. Introduction

Small firms are generally considered as a primary engine of job creation and economic growth by the scientific community and policy makers (Birch, 1987; Davis et al., 1996; Neumark et al., 2011; Haltiwanger et al., 2013). Moreover they can be major generators of innovation and new products, with the potential for creating new industries (Bennett, 2014). For these reasons most governments and international institutions safeguard small firms with special policy treatments, such as more lenient regulations, tax and financial incentives, and programs in support of their growth and innovation processes (see Bennett, 2014, for a discussion of small business policies). Recognising innovation of small firms as a key driver of the renewal of the industrial structure and sustainable economic growth, the European Commission actively supports their innovation capacity via a number of policy instruments, with an allocated budget of 141.6 Euro millions under the Horizon 2020 Work Programme for 2018-2020 (European Commission, 2018).

The economic relevance of small firms is corroborated by the quite regular finding that the growth rate of firms decay with their size. Since the seminal contribution of Gibrat (Gibrat, 1931), a multitude of empirical works has investigated the relation between firm size and growth (for surveys see Santarelli et al., 2006; Coad, 2009). Gibrat postulated that the distribution of firm size should follow a lognormal process, implying independence between firm growth and its size at the beginning of the period. However the majority of empirical tests has rejected the Gibrat law, finding a negative dependence (see *inter alia* Hall, 1987; Evans, 1987b,a; Dunne and Hughes, 1994; McPherson, 1996; Bottazzi and Secchi, 2003; Yasuda, 2005; Calvo, 2006; Colombelli et al., 2013; Grazzi and Moschella, 2018; Arouri et al., 2019), or that the law holds only for firms exceeding a "minimum efficient size" (see *inter alia* Mansfield, 1962; Becchetti and Trovato, 2002; Geroski and Gugler, 2004; Cefis et al., 2006; Lotti et al., 2009; Daunfeldt and Elert, 2013) or beyond the start-up age (Lotti et al., 2001, 2003; Lawless, 2014).

In spite of the abundant research and evidence available, the understanding of the relation between firm size and growth is still limited in a key dimension. In fact, while the main focus of empirical investigations has been on testing whether the law is supported by the data or not, much less attention has been devoted to explore the mechanisms generating the recurrent negative dependence (Daunfeldt and Elert, 2013; Sutton, 1997; Geroski, 1995). A better understanding of the growth drivers of small firms appears crucial to inform policy makers about the most efficient levers to spur their growth.

In this paper we investigate the role of innovation as possible driver of the size-growth relationship using the IQVIAS's MIDAS international database, a unique data set which compiles sales figures for the entire population of firms in the worldwide pharmaceutical industry. This data set has the notable advantage of decomposing firm sales by products in its portfolio, which offers the unique opportunity to directly measure the output of firm innovative activities and to quantify their contribution to the sales growth path. This information is exploited to uncover the role of innovation, in particular

through product switching, in the departure from the Gibrat law. The analysis is performed for the population of 2,173 firms in 21 OECD countries that were active in the period 2002-2008. For this group of firms we observe data for 84,183 products, of which 16,853 are launched and 23,253 are phased out in the period considered.

Innovation, and product switching in particular, appear promising candidates to investigate the size-growth relation. On the one hand, innovation efforts of small and large firms appear significantly different in a number of dimensions (Cohen, 2010; Acs and Audretsch, 1990; Demirel and Mazzucato, 2012). It is generally thought that small firms tend to pursue more product and radical innovations, while large firms focus more on process and incremental innovations (Klepper, 1996; Cohen and Klepper, 1996a,b; Rosen, 1991; Scherer, 1991). Moreover, while R&D expenditure grows monotonically, often proportionally, with size, smaller firms are typically more productive in terms of number of innovations per R&D and size (Cohen, 2010). Some scholars have maintained that R&D productivity declines with size because smaller firms are more capable of innovating (Acs and Audretsch, 1990, 1991) or of generating more significant innovations (Baumol, 2002; Henderson, 1993). Therefore, since innovation has been considered as a major determinant of firm growth, it might be possible that such differences in innovative activities lead to a different growth-premium between small and large firms, possibly accounting for a negative size-growth dependence. However, evidence on the role of innovation in the growth differential by size is rather limited and mixed (Ahn et al., 2018; Demirel and Mazzucato, 2012).

On the other hand, the economic relevance of product switching has been recently emphasized by a growing body of research on multi-product firms. Product switching can have relevant implications for the aggregate economy, such as contributing to a substantial share of aggregate output (Bernard et al., 2010; Broda and Weinstein, 2010), magnifying the amplitude of economic fluctuations (Minniti and Turino, 2013), and sustaining export growth in response to trade liberalization (Timoshenko, 2015). At the firm level, Argente et al. (2019) has recently shown that product flows and life cycle are major determinants of firm growth. Specifically, they find for the US consumer goods sector that the life cycle of products is rather short, and that firms can only grow by continuously adding products whose sales can compensate for the rapid decline of previous products.

The pharmaceutical industry appears of particular interest for analysing the role of innovation in the size-growth relation for a number of reasons. First, R&D investment rates are extraordinary high (Scherer, 2010), and innovation is the major determinant of competitiveness and growth dynamics in the sector, especially via either marginal or radical product innovation (Bottazzi et al., 2001). Second, the division of innovative labour between small and large firms is highly pronounced, with small firms, often biotech related, focusing on the more uncertain process of discovery of niche drugs, and large firms focusing on the marketing and distribution around less innovative drugs (Mazzucato

and Dosi, 2006; Demirel and Mazzucato, 2012).[2] Third, the industry is characterized by quite low levels of concentration and high heterogeneity in terms of firm size (Cefis et al., 2006), and in recent decades small pharma firms have acquired growing importance in terms of diffusion (Demirel and Mazzucato, 2012) and innovative role (Demirel and Mazzucato, 2012; Pammolli et al., 2011; Munos, 2009). Finally, existing tests of the Gibrat law for the pharmaceutical sector do not seem to detect any peculiar pattern, that might excessively limit the representativeness of this sector for the purpose of investigating the size-growth relation; in fact, in line with the general evidence, the Gibrat law is found to hold for samples of large firms (Bottazzi et al., 2001; Cefis et al., 2006), while a negative dependence emerges when smaller firms are included in the sample (Cefis et al., 2006; Demirel and Mazzucato, 2012).

We analyze the contribution of innovation to the relation between firm size and growth by conducting three sets of econometric analyses. First, we test the Gibrat law by implementing an econometric analysis capable to correct for a number of issues raised by previous work. The typical econometric methodology employed by existing studies is well known to be vulnerable to endogeneity (Oliveira and Fortunato, 2006; Colombelli et al., 2013) and firm exit bias (Mansfield, 1962; Evans, 1987b,a; Dunne et al., 1989; Harhoff et al., 1998; Calvo, 2006; Corsino and Gabriele, 2010; Haltiwanger et al., 2013; Grazzi and Moschella, 2018). In the present analysis, we account for both issues by combining Instrumental Variable dynamic panel estimators (Arellano and Bond, 1991) with the correction for sample selection recommended by Wooldridge (2010) for panel data. Furthermore, data sets traditionally employed to test the Gibrat law have often limited or no information on relevant predictors of firm growth – notably age (Haltiwanger et al., 2013) and innovation (Coad, 2009) – therefore it might be possible that higher growth of small firms is driven by the unobserved predictor rather than by small size, with clearly different implications for policy. For example, sometimes the negative size-growth relation disappears when age is controlled for, thus in this case the policy target should be on young rather small firms (Haltiwanger et al., 2013). The data set employed in present analysis allows us to control for age and innovation at the same time. As concerns innovation in particular, the data set allows us to overcome drawbacks in the standard measurement approach by using information on new products and molecules (Bottazzi et al., 2001; Kleinknecht et al., 2002; Hagedoorn and Cloodt, 2003; Corsino and Gabriele, 2010). Results of our best model suggest that a 1% rise in sales leads to a growth penalty of 0.26 percentage points. This finding suggests that the typical counter-Gibrat evidence of a negative size-growth dependence is robust to the proposed corrections.

The main goal of this paper is to investigate the influence of product switching on the size-growth relation. By estimating two separate size-growth equations for firms with a stable portfolio of products

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[2]Examples of less innovative drugs can be drugs with similar therapeutic properties to existing ones, or the so-called "me too" drugs, which are almost identical to existing ones and can be used to extend the monopoly profits of old drugs under a different name.

and firms with flows in the portfolio, we find that the Gibrat law holds for the former, while a negative dependence emerges for latter. We then decompose the growth rate of firms with variable portfolio by the contribution of product flows and stable products, and estimate the relation of each growth component with firm size. We find that, although firm size has no effect on the inflow, outflow, and net flow rate in the number of products, smaller firms launch new products that are larger relatively to existing products in the portfolio. For a given growth rate in the number of products, higher relative sales of new products determine higher jumps in firm size, hence accounting for a negative dependence between firm size and growth. In addition, we find that a negative size-dependence is still present even if sales associated to product flows are removed from firm sales, in contrast with the Gibrat-like behaviour observed for firms with stable portfolio. This evidence suggests that product inflows may have an additional influence operating via externalities on existing products.

Therefore, we examine the relevance of innovation in the two channels through which a negative size-growth dependence is generated. On the one hand, exploiting information on molecular profile, national market, and brand status, we find that new products of small firms tend to be more innovative, and that small firm product innovations contribute to explain the observed negative relation between the market impact of new products and firm size. On the other hand, we find that small firm new products are also more innovative with respect to firm existing products, and that the negative dependence observed for stable products disappears once products that are substitutes of new ones are excluded, indicating larger cannibalization effects for larger firms. Therefore, the present evidence indicates that innovation is a key driver of the emergence of a negative size-growth relation, where the small firm growth-premium is generated either by new-to-world innovation (OECD and Eurostat, 2018), in the form of larger market impact of new products, or by new-to-firm innovation (OECD and Eurostat, 2018), in the form of less pronounced cannibalization by new products.

The paper is organized as follows. Section 2 takes stock of existing approaches used to test the relation between firm size and growth, and to account for the negative dependence observed recurrently. Section 3 describes the data and methods. Sections 4–6 present and discuss results. Section 7 concludes. Additional evidence is reported in the Supplemental Material (SM).

2. Background

This Section provides an overview of the literature on the relation between firm size and growth (Section 2.1), and the negative dependence recurrently observed (Section 2.2). Moreover, it discusses the possible role of innovation in mediating this relation (Section 2.3).

2.1. Tests of the Gibrat law

The Gibrat law is typically tested by estimating a recursive log-linear equation of size, where the interest is on the coefficient of lagged firm size. Estimation of such equation requires much care since

estimates can be flawed by endogeneity and firm exit bias. Endogeneity bias may arise by failure to control for relevant growth determinants that are related with size. Panel data methods have been often used to get rid of this bias (Johansson, 2004; Heshmati, 2001; Van der Vennet, 2001; Del Monte and Papagni, 2003; Bothner, 2005). Unfortunately in dynamic panel models lagged size is necessarily correlated with the idiosyncratic error even after removing the firm fixed effect (Wooldridge, 2010), but empirical applications have often neglected to take this into account. Few studies have employed consistent Instrumental Variables (IV) dynamic panel estimators á la Arellano and Bond (1991) and Arellano and Bover (1995) to correct for this source of endogeneity (Oliveira and Fortunato, 2006; Ribeiro, 2007; Bigsten and Gebreeyesus, 2007; Corsino and Gabriele, 2010; Colombelli et al., 2013). However, no one of these contributions have taken into account simultaneously the sample selection bias arising by firm exit.

Sample selection bias may arise if firm exit is related to characteristics that influence growth as well. This is likely to be case since small firms that have slow or negative growth are more likely to disappear from the sample. After the early prominent contribution made by Mansfield (1962), several studies have accounted for this sample selection bias. Five possible methods have been used in the size-growth literature. First, maximum likelihood methods estimating a growth equation together with a survival equation by Heckman (Harhoff et al., 1998; Lotti et al., 2006; Calvo, 2006; Lotti et al., 2009) or Tobit models (Hall, 1987; Evans, 1987b,a; Dunne et al., 1989; Dunne and Hughes, 1994; Mata, 1994). Second, setting the growth rate of exiting firms equal to -100 (Mansfield, 1962; Bigsten and Gebreeyesus, 2007). Third, comparisons between a group of only surviving firms and the whole sample (Dunne et al., 1989; Bigsten and Gebreeyesus, 2007). Fourth, an ad-hoc definition of growth rate (Davis et al., 1996; Haltiwanger et al., 2013; Lawless, 2014; Grazzi and Moschella, 2018).[3] Fifth, the correction suggested by Wooldridge (2010) for panel models (Corsino and Gabriele, 2010). Results point out that the negative size-growth dependence holds in most cases even after accounting for sample selection. However, these studies have not corrected for endogeneity at the same time.[4]

Size-growth regressions typically include a parsimonious set of control variables reflecting the perception that firm growth rates are to large extent random (Coad, 2009). The predictors of firm sales growth that are considered most important, and hence most widely used in size-growth regressions, are firm age and innovation. Unfortunately data sets employed to test this relationship often contain limited or no information on these variables. Unavailability or poor measures of relevant growth predictors may represent an additional cause of endogeneity, since higher growth of small firms might

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be driven by the unobserved predictor rather than by small size. For example, sometimes the negative impact on growth disappears when firm age is controlled for, thus in this case the policy target should be on young rather small firms (Haltiwanger et al., 2013). Since the role of young firms in fostering aggregate growth has been increasingly emphasized (Schneider and Veugelers, 2010; Pellegrino et al., 2012; García-Quevedo et al., 2014), it appears even more important to purge the size-growth relation of the age contribution. A large number of studies find that firm sales growth decreases with age (see *inter alia* Evans, 1987b,a; Dunne and Hughes, 1994; Geroski and Gugler, 2004; Yasuda, 2005; Haltiwanger et al., 2013; Lawless, 2014; Grazzi and Moschella, 2018; Arouri et al., 2019). Although there are few exceptions reporting a non-monotonic (Barron et al., 1994) or even positive relation (Das, 1995), the negative relation between age and growth appears a quite robust finding.

As regards innovation, several theoretical contributions emphasize its importance for sales growth (Aghion and Howitt, 1992; Geroski, 2000; Klette and Griliches, 2000; Klette and Kortum, 2004; Geroski, 2005). While several empirical studies consistently report a positive effect of innovation on sales growth (Mansfield, 1962; Scherer, 1965; Geroski and Machin, 1992; Geroski and Toker, 1996; Del Monte and Papagni, 2003; García-Manjón and Romero-Merino, 2012; Colombelli et al., 2013; Segarra and Teruel, 2014; Ahn et al., 2018), there also exists a non marginal body of evidence failing to report the expected growth-premium. For example, some studies find a non significant (Geroski et al., 1997; Freel, 2000; Bottazzi et al., 2001) or even negative relation (Coad and Guenther, 2014; Freel and Robson, 2004), while other studies find that the relation depends on the type of firm (Coad et al., 2016; Demirel and Mazzucato, 2012; Stam and Wennberg, 2009; Coad and Rao, 2008).

One reason why the empirical evidence on the effect of innovation on growth is less robust than theoretical expectations may be related to difficulties in measuring innovation (Lööf and Heshmati, 2006; Coad, 2009). The two most popular measures employed, namely expenditure in R&D and patent counts, have a number of drawbacks indeed (Kleinknecht, 1993; Kleinknecht et al., 2002; Lööf and Heshmati, 2006; Coad, 2009; Corsino and Gabriele, 2010). R&D expenditure is only an input of innovation and it may not strongly correlate with the actual innovation output. Moreover the consistent time delay between R&D expenditure and the conversion of the investment into an innovation makes it rather difficult to model its effect on growth. An additional problem can be the under-counting of R&D in small firms (Kleinknecht, 1987). Patent count is a more direct measure of the innovation output but it does not take into account differences in propensity to patent innovations, which may depend on firm size (Brouwer and Kleinknecht, 1999). Moreover, patent count might be an imperfect proxy of the economic impact of innovation as typically only a negligible share of patents has substantial economic impact. A more suitable alternative to R&D expenditure and patent count is the launch of new products (Kleinknecht et al., 2002; Hagedoorn and Cloodt, 2003; Corsino and Gabriele, 2010). In fact, marketed products are a direct measure of the innovation output and translate into

a concrete cash-flow. Moreover, this definition is used to represent innovation in many theoretical models of growth (Kalecki, 1945; Simon and Bonini, 1958; Fu et al., 2005; Bottazzi et al., 2001; Growiec et al., 2008, 2018). Unfortunately information on new products is relatively rare in empirical data used to test size-growth regressions and only a handful of studies were able to use this measure (Roper, 1997; Calvo, 2006; Corsino and Gabriele, 2010; Colombelli et al., 2013; Coad and Guenther, 2014). Furthermore it is even more rare to have information to discriminate products on the extent of their innovation (Bottazzi et al., 2001). Note that while the launch of new products can be a valid proxy for product innovation, it does not capture process innovation. The role of process innovation is beyond the scope of the present analysis.

Another possible limitation of size-growth regressions is the lack of controls for the firm technological profile. For example, a large body of research has analysed the relation between firm diversification and performance. Theoretical models and empirical investigations generally suggest that diversification has a positive impact on firm growth, although the effect appears to revert for very high levels of diversification, giving rise to an inverted U-shape relation (for surveys see Palich et al., 2000; Wan et al., 2011). Despite the prominent role ascribed to diversification as determinant of firm growth, this variable has been typically neglected in size-growth regressions. In addition, size-growth regressions normally do not take into account technological change arising by a reallocation of resources across technological domains, and not by innovation. Such form of technological change can reflect a more efficient combination of resources and hence it might be a relevant predictor of firm growth (Nason and Wiklund, 2018).

2.2. Explanations of the negative size-growth dependence

A number of rationales have been put forward in the literature to explain why smaller firms exhibit higher growth rates. They generally ascribe the negative dependence to scale disadvantages that force small firms to grow in order to reduce average costs and hence increase their likelihood to survive (Strotman, 2007; Acs and Audretsch, 1990).

The traditional paradigm posits that market selection leads inefficient firms to decline and fail, and efficient firms to grow and survive, promoting a long-run equilibrium where a core of firms have reached the Minimum Efficient Size (MES) and prevalently exhibit a Gibrat-like behaviour (Lotti et al., 2006, 2009; Daunfeldt and Elert, 2013; Rossi-Hansberg and Wright, 2007). This evolutionary paradigm reconciles the wealth of evidence rejecting the Gibrat law with earlier supporting evidence based on samples of well-established, mature and large firms (Lotti et al., 2009). It is also in line with evidence that rejection is more likely to arise in industries with higher MES, where the scale disadvantage is larger (Daunfeldt and Elert, 2013; Audretsch et al., 2004). The evolutionary account has been theoretically rooted (Lotti and Santarelli, 2004; Lotti et al., 2009) in models of learning in

which entrants are uncertain about their relative level of efficiency, and learn their growth potential by observing their profit realization (Jovanovic, 1982; Ericson and Pakes, 1995; Audtretsch, 1995).

Cabral (1995) also demonstrated that the negative dependence arises in a model with sunk costs, since higher likelihood to exit the market leads small entrants to invest in capacity more gradually, which results in higher expected growth than larger entrants. In the model of Cabral (1995), an alternative mechanism is represented by financial constrains of small entrants, since they should become less and less binding after start-up age and hence lead small entrants to grow more rapidly.

2.3. The role of innovation in the size-growth relation

A problem with existing rationales of the negative size-growth dependence is that the economic drivers of the underlying mechanisms are difficult to test empirically. In this paper we explore the role of innovation, in particular product innovation, as a possible explanation of such dependence. Innovation appears as a possible candidate since it is considered a major determinant of firm growth, and innovative efforts of small and large firms differ significantly in a number of dimensions (Cohen, 2010; Acs and Audretsch, 1990; Demirel and Mazzucato, 2012). First, small and large firms generally conduct different types of innovative activities. It is generally thought that small firms tend to pursue more product and radical innovations, while large firms focus more on process and incremental innovations (Klepper, 1996; Cohen and Klepper, 1996a,b; Rosen, 1991; Scherer, 1991). Different types of innovations may have different implications for firm performance and growth (Cohen and Klepper, 1996a; Gunday et al., 2011; Koellinger, 2008; Varis and Littunen, 2010; Atalay et al., 2013; Bianchini et al., 2016; Guarascio and Tamagni, 2016; Pérez et al., 2019). While there exist some evidence suggesting that product innovation outperforms process innovation (Cohen and Klepper, 1996a; Bianchini et al., 2016; Guarascio and Tamagni, 2016), or that radical innovation outperforms incremental innovation (Rubera and Kirca, 2012) in terms of market impact, evidence on the relative performance of different types of innovation is in general inconclusive.

Second, a large body of research on the relation between firm size and innovative performance has documented a size-penalty in spawning innovations (for a survey see Cohen, 2010). A quite robust finding in this literature is that R&D expenditure rises monotonically, in general proportionally, with size among R&D performers. However several studies have reported that smaller firms are more productive than larger firms in terms of number of innovations (patents, reported innovations, new products or others) per R&D unit, and that they generate a disproportionately large share of innovations relative to their size (Acs and Audretsch, 1987, 1998, 1990, 1991; Bound et al., 1984; Pavitt et al., 1987; Cohen and Klepper, 1996a; Geroski, 1994; Graves and Langowitz, 1993; Lerner, 2006). Some scholars have maintained that R&D productivity declines with size because smaller firms are more capable of innovating (Acs and Audretsch, 1990, 1991) or of generating more significant or

breakthrough innovations (Baumol, 2002; Henderson, 1993).[5]

The literature has proposed a number of arguments to explain why small firms might be in an advantageous position for undertaking innovative activities (see Cohen, 2010; Acs and Audretsch, 1990). These arguments generally refer to differences in the management structure of small and large firms. The bureaucratic organization of large firms may limit undertaking of risky R&D, and may hinder the performance of scientists, through excessive bureaucracy or lower managerial control. Moreover, in large firms the incentives of scientists and entrepreneurs may be limited by their lower ability to reap the benefits of their efforts or by the conservative attitude typical of large corporations hierarchies.

Although a relevant strand of literature has pointed out a possible small firm innovative advantage, existing evidence on the role of innovation in generating a sales growth differential by size is rather limited and mixed. For example, while Hay and Kamshad (1994) report that investment in product innovation is the most popular strategy for expansion used by Small-Medium Enterprise (SME) managers in many industries, Freel and Robson (2004) find that product innovation (both incremental and novel) has even a negative effect on sales growth for a sample of manufacturing SME.[6] Moreover, while Ahn et al. (2018) find that R&D expenditure has positive impact on sales growth for a sample of SME, Demirel and Mazzucato (2012) find for the pharmaceutical sector that R&D expenditure has positive impact on sales growth for a sample of large firms, but not significant impact for a sample of small firms, unless they are persistent patentees. Daunfeldt and Elert (2013) test the hypothesis that small firms in innovative sectors have higher growth than large firms, however they find no statistical association between the R&D revenue share and the probability that the Gibrat law holds in the sector.

3. Data and methods

3.1. Data

We make use of the MIDAS international database maintained by IQVIA,[7] which contains detailed sales data for the entire population of firms in the worldwide pharmaceutical market.[8] This database provides information on worldwide sales for each single pack of pharmaceutical products on a quarterly

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[5]Cohen and Klepper (1996a,b) suggested that a declining R&D productivity might not reflect a relative inefficiency of large firms: they proposed that it is efficient for larger firms to invest more in R&D because they can spread the fixed cost over a higher level of output, hence earning higher profits per unit of R&D despite the R&D technology might have diminishing returns.

[6]Freel and Robson (2004) find also that (incremental) process innovation has positive effect for service SME.

[7]IQVIA, formerly Quintiles and IMS Health, is a leading global information and technology services company, that independently collects data on the sales and marketing of pharmaceutical products, by tracking prescription pharmaceutical purchases made by hospitals and by retailers.

[8]Data are available for the following 21 countries: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovenia, Sweden, UK, USA.

basis. We base our analysis on yearly sales for the population of 2,173 firms that were active in the period 2002-2008.[9]

The key advantage of this dataset is availability of identifiers for firms, products, and molecules. These identifiers allow creating figures of firm sales and their decomposition by products, further discriminating between products associated to new or existing molecules. Information on product allows having a direct measure of the output of firm innovative activities and to quantify their contribution to the firm growth path. Information on new molecules allows identifying products associated to major innovations.

The data contain also information on the drug Anatomical Therapeutic Chemical (ATC) classes. The ATC classification system divides drugs into different groups according to the organ or system on which they act and/or their therapeutic and chemical characteristics.[10] ATC classes can be exploited to create measures of firm diversification and technological change.

An additional advantage of this data set is that firms going through mergers or acquisitions are treated as if they were a unique entity from their birth and their sales data are consolidated retroactively. This implies that abrupt jumps in size or disappearance from the sample associated to such events are ruled out, which avoids possible measurement error in modeling the processes of growth as well as exit from the market in the econometric analysis. This appears a significant advantage also in light of the particular focus on innovation, because it is quite common to observe large pharmaceutical companies buying out smaller innovative firms, especially in biotech.

3.2. Econometric model

The Gibrat law postulates that the growth rate of a firm should be independent of its size at the beginning of the period. The starting point of the typical econometric approach is the following equation:

$$ln(S_{i,t}) - ln(S_{i,t-1}) = \beta ln(S_{i,t-1}) + X_{i,t}\delta + \omega dt_t + \mu_i + u_{i,t} \tag{1}$$

where $S_{i,t}$ are firms yearly sales[11], dt_t are $T-1$ year dummies, μ_i is the firm fixed effect, $u_{i,t}$ is an idiosyncratic error term, and $X_{i,t}$ is a matrix of regressors. The coefficient β is the "Gibrat coefficient"; the Gibrat law holds only if $\beta = 0$.

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[9]We consider aggregated yearly sales to avoid seasonality issues. For packs that are born or disappear within the sample period, the four quarterly observations may not be all available in the year they are born or disappear, therefore their corresponding yearly sales are set to missing to avoid spurious jumps.

[10]The system is articulated in the following five levels: (1) main anatomical group, (2) main therapeutic group, (3) therapeutic/pharmacological subgroup, (4) chemical/therapeutic/pharmacological subgroup, (5) chemical substance.

[11]Firm growth has been typically measured by using indicators such as sales, employment, or assets. Consistently with the majority of studies investigating the impact of innovation on firm growth, sales appears the most appropriate indicator for our purpose of exploring the role of innovation in the size-growth relation (Colombelli et al., 2013).

Equation 1 can be rewritten as

$$ln(S_{i,t}) = \tilde{\beta}ln(S_{i,t-1}) + X_{i,t}\delta + \omega dt_t + \mu_i + u_{i,t}, \tag{2}$$

where $\tilde{\beta} = 1 + \beta$. Equation 2 makes it clear that estimating Equation 1 is equivalent to estimating a dynamic equation of logarithmic sales with a lagged-dependent variable on the right-hand side. We estimate Equation 2 but interpretation of parameters can be more easily recovered from Equation 1. Estimates of parameters δ are to be interpreted as effects on the sales growth since are estimated in Equation 2 for given $ln(S_{i,t-1})$. Testing for $\tilde{\beta} = (>,<)1$ in Equation 2 is equivalent to testing for $\beta = (>,<)0$ in Equation 1.

3.3. Explanatory variables

The data used in the present analysis allows to create direct and meaningful measures for the most important growth predictors, namely age and innovation. Additionally, it allows creating proxies for the firm diversification strategy and technological change. In the rest of this section we discuss our measurement approach.

We define the variable $age_{i,t}$ for firm i in year t as the age of its oldest product pack, making use of the launch date. We include age dummies to capture possible non-monotonicity in the relation.

The data set allows to overcome several limitations in modeling the relation between innovation and growth. First it contains information on products and hence we can measure innovation by tracking flows of products. Namely we use the variable k^{in}, defined as $K_{i,t}^{in}/K_{i,t-1}$ where $K_{i,t-1}$ is the total number of products marketed in year $t-1$ and $K_{i,t}^{in}$ is the number of new products in t. In order to take into account exhaustion of the economic impact of innovations, we also include the variable k^{out}, defined as $K_{i,t}^{out}/K_{i,t-1}$ where $K_{i,t}^{out}$ is the number of products lost by the $i-th$ firm in year t. Another advantage of the data is availability of identifiers for molecules, which can be used to discriminate new products on the basis of their innovative content. Therefore we create a third innovation variable, $newmol_{i,t}$, a dummy that discriminates between firms launching new products with new-to-firm molecules ($newmol = 1$) and firms launching new products with molecules already marketed by the firm ($newmol = 0$). Note that this indicator does not discriminate between molecules already marketed by other firms and new-to-world molecules, while the latter are supposed to be more radical and possibly more impactful innovations. An indicator for these specific molecules could not be used as an explanatory variable in the econometric analysis because such innovations are observed quite rarely (Bottazzi et al., 2001; Munos, 2009). Descriptive statistics on molecule-based innovations by firm size will be presented in Section 5.

Finally, we exploit information on drug ATC classes to create additional regressors reflecting the diversification strategy and the technological change of the firm. These measures are based on the

first four digits of the ATC code, which correspond to the third level of the classification and indicate the chemical, therapeutic or pharmacological subgroup of the drug. 687 classes are observed in the data according to this definition. Decomposing firm sales by ATC classes of its drugs, we define the principal ATC class of a firm as the class associated to the largest sales share.

In the present analysis we take diversification into account by creating the variable $atcmain_{i,t}$, defined as the share of firm sales associated to the firm principal ATC class. High levels of $atcmain_{i,t}$ imply that firm sales are highly concentrated in a pharmaceutical class and hence the firm is considered to have a low degree of diversification.

We proxy technological change by the variable $atcD_{i,t}$, a dummy indicating whether the firm principal ATC class changes from $t-1$ to t. This variable captures the growth effect of a major change in the firm technological profile. In general a major technological change may be associated to significant innovations or products decline that can be reflected in the regressors k^{in}, $newmol$, and k^{out}. However it may be also associated to redistribution of resources across pharmacological classes. Therefore the purpose of this variable is to explain additional variation in growth arising by technological change that might not be accounted for by changes in the product portfolio. Such form of technological change can reflect a more efficient combination of resources and hence it might be a relevant predictor of firm growth.

Table 1 provides summary statistics on the sample used in the analysis. Yearly sales $S_{i,t}$ are expressed in British pounds of 2006. We notice that in the whole sample the average firm has 105.1 million sales, 33.4 products, a negative growth rate of 5.5%, it is around 35 years old, and it has a 1.8% likelihood to drop off the sample in a given year. Moreover we notice that there is a positive trend in average sales over years although the average growth rates is always negative: this pattern is likely driven by small firms dropping off the sample.

3.4. Estimation method

Estimation of Equation 2 requires much care because of the presence of the lagged dependent variable on the right hand side, which may lead to endogeneity bias, and because some firms may drop out of the sample during the reference period, possibly leading to selection bias. In this section we discuss how we take into account potential endogeneity (Section 3.4.1) and firm exit bias (Section 3.4.2).

3.4.1. Endogeneity

In estimating the relation between firm growth and size there might be two possible sources of endogeneity. First, right hand side variables may be correlated with the fixed effect μ_i. In dynamic panel data this source of endogeneity arises necessarily because $ln(S_{i,t-1})$ is positively correlated with the fixed effect μ_i, and this correlation does not vanish as the number of cross sections or time periods get larger (Bond, 2002). Standard results indicate an upward bias of pooled OLS estimates of $\tilde{\beta}$ in

Equation 2 (Bond, 2002). This source of endogeneity is normally corrected for with panel data by wiping out the fixed effects through ad hoc transformation of data, such as Fixed-Effects (FE) or First Differences (FD) transformations. After data transformation, the estimand equation becomes as follows:

$$s_{i,t}^* = \tilde{\beta} s_{i,t-1}^* + X_{i,t}^* \delta + u_{i,t}^*, \tag{3}$$

where the apex * denotes transformed data. The typical panel approach consists in applying pooled OLS to this equation.

A second source of endogeneity arises by applying pooled OLS to Equation 3, due to presence of $ln(S_{i,t-1})$ on the right hand side of Equation 2. In fact, the lagged dependent variable and the idiosyncratic error term are necessarily correlated both in Equation 2 and in the transformed Equation 3. In Equation 3, $s_{i,t-1}^*$ and $u_{i,t}^*$ are correlated because concomitant values of $s_{i,.}$ and $u_{i,.}$ are present in $s_{i,t-1}^*$ and $u_{i,t}^*$, respectively (Bond, 2002). In the FE case, the estimation bias arising by such correlation is invariably negative for $\tilde{\beta} > 0$, and may become negligible only if T is relatively large, which is not the typical case in micro panels (Nickell, 1981; Judson and Owen, 1999).[12] Therefore, a downward bias can be expected in FE estimates of $\tilde{\beta}$ in Equation 2 (Bond, 2002).

A way to get consistent estimates of Equation 2 is to apply Instrumental Variables (IV) methods to the transformed Equation 3. In applying IV methods to the transformed equation it is more advantageous to use the FD transformation because, unlike the FE transformation, FD does not introduce all realizations of the error term series into the error term of the transformed equation in t (Anderson and Hsiao, 1982). This condition, together with the assumptions of no autocorrelation in $u_{i,t}$, implies that lags of the dependent variable other than $ln(S_{i,t-1})$ are orthogonal to $u_{i,t}^*$ in the transformed equation and hence plausible IVs (Arellano and Bond, 1991; Bond, 2002). Under these conditions, $ln(S_{i,t-2})$ and $\Delta ln(S_{i,t-2})$, for example, are mathematically related to $\Delta ln(S_{i,t-1}) = \equiv ln(S_{i,t-1}) - ln(S_{i,t-2})$ but not to the error term $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$ in Equation 3, hence satisfying relevance and exogeneity conditions for valid IV. Natural candidate IVs can be $ln(S_{i,t-2})$, $\Delta ln(S_{i,t-2})$, $\Delta X_{i,t-1}$ and further lags of these variables (Arellano and Bond, 1991). Therefore, we estimate Equation 3 using the FD transformation and employ either the two stage least squares (Anderson and Hsiao, 1982) or two-step GMM estimator (Holtz-Eakin et al., 1988; Arellano and Bond, 1991). The following list of IVs is used in estimation trading-off between explanatory power and time periods available for estimation: $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$, $\Delta ln(S_{-4})$. Since absence of autocorrelation is crucial for the validity of these IVs, autocorrelation tests will be discussed and presented in the results section (Arellano and Bond,

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[12]In the fixed effect case one has $s_{i,t-1}^* = s_{i,t-1} - \frac{1}{T_i-1}(s_{i,1} + \ldots + s_{i,t} + \ldots + s_{i,T_i})$ and $u_{i,t}^* = u_{i,t} - \frac{1}{T_i-1}(u_{i,2} + \ldots + u_{i,t-1} + \ldots + u_{i,T_i})$. The component $-\frac{s_{i,t}}{T_i-1}$ in $s_{i,t-1}^*$ is correlated with $u_{i,t}$ in $u_{i,t}^*$, and the component $-\frac{u_{i,t-1}}{T_i-1}$ in $u_{i,t}^*$ is correlated with $s_{i,t-1}$ in $s_{i,t-1}^*$. If T_i were large the component above would be negligible and the correlation would disappear.

1991). Note that if the error terms $u_{i,t}$ are correlated of order 1, then $ln(S_{i,t-2})$ is correlated to $u_{i,t-1}$ and hence to the FD errors $u_{i,t}^* = u_{i,t} - u_{i,t-1}$, making it a potentially invalid IV. However, $ln(S_{i,t-3})$, $\Delta ln(S_{i,t-3})$ and further lags would be still valid IVs, unless order-2 serial correlation is found, in which case valid IVs would start from even longer lags (Bond, 2002).

3.4.2. Firm exit

A sample selection bias may arise in this setting if selection out of the sample depends on firm characteristics influencing also the response variable, even after explanatory variables are controlled for. In our case it is likely that firm exit depends on sales, age and innovation. We correct for this source of bias by employing the two-step procedure recommended by Wooldridge for panel data (Wooldridge, 2010, pp. 837). Following the terminology of Wooldridge, we will refer to this form of sample selection as "attrition". The procedure consists in estimating a sequence of selection probit model for each time period t:[13]

$$P(I_{i,t} = 1 | W_{i,t}, I_{i,t-1} = 1) = \Phi(W_{i,t}\gamma_t), \quad t = 2 \ldots T, \tag{4}$$

where $I_{i,t}$ is a selection indicator equal to 1 if $(ln(S_{i,t}), X_{i,t})$ are observed in t, and $W_{i,t}$ must contain variables observed at time t for all units with $I_{i,t-1} = 1$. Good candidates for $W_{i,t}$ can be $ln(S_{i,t-2})$, $X_{i,t-1}$, and further lags of these. In fact, if Equation 2 is dynamically complete, $ln(S_{i,t-2})$ and $X_{i,t-1}$ are orthogonal to $\Delta u_{i,t}$ and hence can be valid instruments. We include in $W_{i,t}$ the following variables: $ln(S_{-2})$, $Age = 11 - 20$, $Age = 21 - 50$, $Age > 50$, k_{-1}^{in}, k_{-1}^{out}, k_{-2}^{out}, $ln(atcmain)_{-1}$. $ln(S_{-2})$, k_{-1}^{out} and k_{-2}^{out} can be included in $W_{i,t}$ because they are not significant in Equation 2.

After estimating the selection probit for each year we compute the inverse Mills ratio $\hat{\lambda}_{i,t}$.[14] Interactions between year dummies and the estimated inverse Mills ratio are then plugged in Equation 3 to estimate the following equation:

$$s_{i,t}^* = \tilde{\beta} s_{i,t-1}^* + X_{i,t}^* \delta + \rho_t \hat{\lambda}_{i,t} dt_t + \gamma dt_t + u_{i,t}^*. \tag{5}$$

The FD transformation turns out to be particularly suitable in this case due to the sequential nature of attrition (see Wooldridge, 2010, pp. 837). Equation 5 can be estimated by instrumental variables on the selected sample. A simple test for attrition bias is a Wald test for $\rho_t = 0$ ($\forall t$) in Equation 5. If the null hypothesis of absence of attrition bias is rejected, $\hat{\lambda}_{i,t} dt_t$ need to be maintained in Equation 5. Standard errors of parameters in Equation 5 are estimated by panel bootstrap method because the

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[13]In this procedure attrition is treated as an *absorbing state*, so that once a firm drops out it will never re-enter the sample.

[14]The inverse Mills ratio is defined as $\lambda \equiv \frac{\phi(c)}{\Phi(c)}$ where ϕ denotes the standard normal density function, and Φ is the standard normal cumulative distribution function

equation contains generated regressors (Wooldridge, 2010).

4. Results: the relation between size and growth

In this section we report estimates of Equation 2, which models the relation between firm size and growth. Estimates are reported in Table 2. The first two models of Table 2 report pooled OLS and FE estimates, which do not account for endogeneity of lagged sales. OLS and FE estimates must be biased, however they are reported for a preliminary inspection of the reliability of IV estimators, because they can indicate an upper (OLS) and lower (FE) threshold for consistent estimates of $\tilde{\beta}$. OLS estimate is equal to 1.024 and significantly higher than 1, while FE estimate is equal to 0.798 and significantly lower than 1; therefore the Gibrat law is rejected in both cases but in opposite direction. Remark that a 95% confidence interval can be constructed by subtracting and adding to the coefficient 1.96 times the standard error.

The following models of Table 2 report IV dynamic panel estimates, either without or with correction for attrition. FD-2S and GMM estimates of $\tilde{\beta}$ without correction for attrition fall within the OLS-FE interval (FD-2S=0.824, FD-GMM=0.862), as one would expect if the AR(1) model in Equation 2 provides a good representation for S_t and FD-2S and GMM estimators are not subject to any serious finite sample bias (Bond, 2002). Both point estimates are significantly lower than 1, suggesting a negative relation between size and growth. The last two columns of the Table report 2S and GMM estimates of Equation 5, where attrition is taken into account. After this correction, 2S and GMM estimates of $\tilde{\beta}$ drop to 0.713 and 0.735, respectively, leading to an even stronger rejection of the Gibrat's hypothesis. This correction has a relevant impact on $\tilde{\beta}$ estimates, suggesting that size is an important predictor of firm attrition. In fact, as it is showed in Table SM1 in Section SM2 reporting estimates of the yearly selection equation, $ln(S_{-2})$ has a positive and strongly significant impact on the firm survival probability. FD-GMM-ATT is selected as best model over FD-2S-ATT because the GMM estimator is asymptotically efficient in the class of dynamic panel estimators (Ahn and Schmidt, 1995; Arellano and Bover, 1995). However evidence that 2S and GMM estimates are similar provides support to the robustness of our estimates.[15]

In IV dynamic panel estimation, diagnostic tests represent a particularly important toolkit to assess models validity. In Table 3 we report several tests for the best model (FD-GMM-ATT). First, the presence of attrition is confirmed by rejection of the Wald test of $\rho_t = 0$ (see Equation 5).[16] Second,

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[15]We also estimated models with a set of "GMM-style" instruments in line with the formal representation of the difference GMM (Arellano and Bond, 1991) and system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) estimators. These estimators can deliver gains in terms of sample size and efficiency at the cost of potential over-fitting of endogenous variables due to instrument proliferation (Roodman, 2009). These models were not reported because their diagnostics was outperformed by models with a more parsimonious set of instruments such as 2S and standard GMM.

[16]This finding is corroborated by a further test we performed adding the lagged selection indicator $I_{i,t-1}$ to Equation 3 and estimating by fixed effects. A statistically significant coefficient of $I_{i,t-1}$ allowed us to reject the null hypothesis of

the Arellano-Bond autocorrelation test (Arellano and Bond, 1991) suggests that the model does a good job in removing autocorrelation. This statistic tests for autocorrelation in $u_{i,t}$ by testing for lack of second-order autocorrelation in the FD residuals $\Delta u_{i,t}$. In fact, if errors are not autocorrelated in levels, negative AR(1) is expected in FD residuals because $u_{i,t}$ compare both in $\Delta u_{i,t}$ and $\Delta u_{i,t-1}$, but AR(2) is certainly absent (Arellano and Bond, 1991). Indeed, Table 3 shows that AR(1) is negative and significant as expected, but AR(2) is not significant, nor AR(3). This finding is crucial for the validity of the identification strategy, since IVs exogeneity rests on the absence of autocorrelation. Third, the F-test of IVs in the first-stage regression is fairly large and significant suggesting that IVs are strong.[17] In addition, first-stage regression results show that IVs are highly significant also individually. First-stage regression results for IV models in Table 2 are reported in Section SM3 (Table SM6) together with first-stage results for other IV models presented later. Fourth, the under-identification test is highly significant suggesting rejection of the null hypothesis of IVs redundancy. Fifth, the underidentification test remains significant even if redundancy is tested on the IVs individually. Sixth, the overidentification test is not significant with a very large p-value, suggesting that the null hypothesis of IVs exogeneity cannot be rejected. Finally, evidence of IVs exogeneity holds even if the overidentification test is carried out on IVs individually.

In light of results and diagnostics from our best model, we can conclude that the Gibrat hypothesis is rejected in our data, supporting the typical negative size-growth relation. FD-GMM-ATT estimate of $\tilde{\beta}$ reported in Table 2 suggests that a one-percent rise in sales of last year increases current sales by 0.735% (C.I 5%: $0.632 - 0.837$), *ceteris paribus*. The corresponding growth effect amounts to $(\tilde{\beta} - 1) = -0.265$, suggesting a penalty in the growth rate of 0.265 percentage points.

Coefficients of the other regressors are plausible in sign and magnitude. We find a negative age effect as mostly observed is similar studies. Namely, the youngest age group ($Age \leq 10$) has the highest growth rate, although the effect size is similar across older groups, and significance is found only in comparison with the age bracket $11 - 20$. k^{in} and k^{out} have, respectively, a positive and negative impact on growth. The impact of k^{in} persist up to the first lag, while k^{out}_{-1} was not significant and hence excluded. *newmol* has a quite long-lasting positive effect on growth, with the strongest impact one year later. Consistently with theoretical predictions, the positive impacts of k^{in} and *newmol* suggest that innovation enhances growth both by the quantity and quality of innovations, while previous studies failed to report such effects. $ln(atcmain)$ has negative coefficient, implying that concentration (respectively diversification) is detrimental (respectively beneficial) to firm growth, as

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no attrition (see Wooldridge, 2010, pp. 837).

[17]Note that the reported F-statistic is the Kleibergen-Paap statistic, which can be used to test for weak identification. Weak identification arises when the excluded instruments are correlated with the endogenous regressors, but only weakly, in which case estimators can perform poorly (Stock and Yogo, 2005). Stock and Yogo (2005) tabulated critical values for weak identification tests. For our case, the critical values for 5% maximal IV relative bias and 10% maximal IV size are, respectively, 13.91 and 22.30. Therefore, with $F = 113.73$ we can safely reject the null hypothesis that the IVs are weak.

consistent with a large body of evidence. Finally, $atcD_{-1}$ has positive effect, confirming the theoretical expectation that a technological change, as captured by a change in the firm major pharmaceutical class, is beneficial to growth.

5. Results: the role of product flows in the relation between size and growth

In this section we explore the contribution of product flows to the departure from the Gibrat law reported in the previous section. To this aim, we first decompose the sample in two sub-samples of firms with either a stable portfolio of products or with a variable portfolio, and analyze the size-growth relation in these two samples separately (Section 5.1). Then, we examine in more detail the channels through which product flows may influence the size-growth relation (Section 5.2).

5.1. Firms with stable and variable portfolio of products: a comparison

The sample of firms with stable portfolio (SP) is defined by all firms with an invariant set of products throughout the period under investigation. The sample of firms with variable portfolio (VP) comprises the residual sample of firms experiencing at least one inflow or outflow. In Table 4 we report estimates of the size-growth Equation 2 for these two sub-samples separately. For the SP sample, the regressors k^{in}, k^{out}, $newmol$, and $atcD$ are always equal to zero by construction, therefore they have been removed from the list of controls. The set of instrumental variables (IV) is the same in both cases and equal to the set used for the full sample. IV first-stage regression results are reported in Section SM3 (Table SM7), and estimates of yearly selection equations are reported in Section SM2 (Tables SM2–SM3).

FD-GMM estimates of $\tilde{\beta}$ after controlling for attrition are respectively 0.685 for the VP sample, and 0.904 for the SP sample. In the SP sample the Gibrat coefficient is somewhat larger and not even significantly lower than 1, therefore the Gibrat's hypothesis of independence between size and growth cannot be rejected in this case. Conversely, the negative dependence is significant for VP firms and stronger in magnitude with respect to the full sample. Diagnostic tests for FD-GMM-ATT models are reported in the Supplemental Material (Table SM22). Diagnostics suggest that FD-GMM-ATT models perform quite well in both cases. Only few concerns emerge with respect to the IV $\Delta ln(S_{-4})$: in the SP sample, the IV is not significant in the first-stage equation (see Table SM7 in Section SM3) and the redundancy test is not significant as well ($p = 0.4$); in the VP sample, the IV appears relevant but the exogeneity test is close to rejection at the 5% significance level ($p = 0.07$). Since such limitations might influence our results, the models were estimated also without this particular IV. Estimates are reported in the Supplemental Material (Table SM15), together with diagnostic tests (Table SM23) and first-stage results (Table SM8). FD-GMM-ATT estimates of $\tilde{\beta}$ change minimally (respectively, from 0.904 to 0.915 and from 0.685 to 0.650) and the diagnostics works fine for both samples. Overall, the key finding that the negative dependence holds only for VP firms appears robust.

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Since SP firms exhibit a Gibrat-like behaviour, while VP firms exhibit a counter-Gibrat behaviour, products switching appears a key driver for the failure of the Gibrat law, and in particular for the emergence of a negative size-growth relation. It is hence of interest to examine the characteristics of these two groups of firms. Table 5 provides summary statistics for the two sub-samples together with the full sample. Statistics show that, on average, SP firms are small ($S = 1.4$ millions) and have typically one or few products ($K = 1.5$), while VP firms are large ($S = 124.5$ millions) and have many products ($K = 39.4$). The former are also younger (21.1 vs 37.3 years), although well above the start-up age, and have lower sales growth (-14.4% vs -3.8%) as well as higher exit rate (4.9% vs 1.2%). This evidence points out that the two types of firms do not correspond, and are even almost opposite, to the prototypes that the traditional evolutionary paradigm has identified to explain the Gibrat-like and counter-Gibrat evidence. According to this argument, the negative relation holds only for small and less established firms that are forced to grow fast to avoid exit, but it disappears once learning processes and market selection have generated a core of large, mature and well-established firms (Lotti et al., 2006, 2009; Daunfeldt and Elert, 2013). Conversely, our findings suggest that a Gibrat-like behaviour can be observed for small and slow growing firms, provided they keep a stable product portfolio, and a counter-Gibrat behaviour can be observed for large, more mature and faster-growing firms, provided they are active in product switching. Therefore, although our evidence does not contradict the traditional paradigm, it points out the role of product flows as an alternative mechanism underlying the emergence of a negative size-growth dependence.

5.2. Firms with variable portfolio: decomposing the growth effect of product flows

In this section we examine in more detail the channels through which product flows may lead to a negative size-growth relation. Therefore, we restrict the analysis to the sample of firms with variable portfolio, for which only such negative dependence appears to hold. This sample is also quantitatively more relevant, accounting for almost 80% of all firms. The contribution of product flows is detected by decomposing the firm growth rate in its constituents and studying how product flows can mediate their relation with firm size.

The growth decomposition is operationalized by expressing firm size as $S = K \cdot \overline{S}$, where K is the number of firm products, and $\overline{S} \equiv S/K$ are the average sales of firm products. With this definition, the firm sales growth rate g_S can be decomposed as $g_S = g_K + g_{\overline{S}}$, where g_K is the growth rate of K, and $g_{\overline{S}}$ is the growth rate of $\overline{S}$.[18] This decomposition makes it clear that product flows can lead smaller firms to grow faster in sales either by (i) higher growth in the number of products (g_K), by (ii) higher growth in product average sales ($g_{\overline{S}}$), or by a combination of (i) and (ii). In order to assess

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[18]Since $S = K \cdot \overline{S}$, the sales growth rate $g_S \equiv ln(S) - ln(S_{-1})$ can be written as $g_S = ln(K \cdot \overline{S}) - ln(K_{-1} \cdot \overline{S}_{-1}) = ln(K) - ln(K_{-1}) + ln(\overline{S}) - ln(\overline{S}_{-1}) = g_K + g_{\overline{S}}$, where $g_K \equiv ln(K) - ln(K_{-1})$, and $g_{\overline{S}} \equiv ln(\overline{S}) - ln(\overline{S}_{-1})$.

the importance of the two possible channels, we analyse the relation between the two growth rates and S. These analyses are discussed in turn in the rest of this Section.

First, we estimate a recursive model for K to test the effect of S on the growth rate of K. One can think of this model as a size-growth equation similar to Equation 2, where K is used as a proxy for size in place of S, and $ln(S_{-1})$ is included in addition as control variable. Table 6 reports estimates of the usual model variants. Lags of first-differences (FD) of the dependent variable are used as IVs similarly to models for g_S. However, $\Delta ln(K_{-2})$ was replaced by $\Delta ln(S_{-2})$ in this case because it did not pass the exogeneity test, leading to the following list of IVs: $\Delta ln(K_{-3})$, $\Delta ln(K_{-4})$ $\Delta ln(S_{-2})$. Results show that FD-2S and FD-GMM estimates of $\tilde{\beta}$ are significantly lower than 1 (FD-2S=0.695, FD-GMM=0.748) and within the FE-OLS bounds (FE=0.625, OLS=0.944). After correcting for attrition, these estimates change only modestly, in contrast to estimates of size-growth equations in S. This result is consistent with the outcome of the attrition test, which provides no evidence of attrition in this case (see tests for the FD-GMM-ATT model in Table SM24 in Section SM5). Absence of attrition derives by the fact that K is a weak predictor of the firm survival probability, unlike S, as suggested by estimates of the selection equations reported in Section SM2 (Table SM4). In fact, we note that while $ln(S_{-2})$ is always strongly significant, $ln(K_{-2})$ is significant only in some years.

Since there is no evidence of attrition, the efficient FD-GMM model is considered as the best model for the size-growth equation in K. The FD-GMM estimate suggests a negative dependence between the growth rate and the number of products, similarly to the size-growth relation in sales. Turning to the effect of size, the coefficient on $ln(S_{-1})$ is not significantly different from 0, suggesting that size does not influence the growth rate of K. It follows from this result that the negative dependence between growth and size measured in firm sales does not appear to derive by a small firm advantage in the growth rate of K. The validity of FD-GMM estimates is supported by the diagnostic tests reported in Table SM24. See also Section SM3 (Table SM9) for IV first-stage regression results.

As a second piece of analysis, we examine the relation between firm size (S) and the growth in the average size of firm products $g_{\overline{S}}$. If we consider a market where firms grow in K at a rate that is independent of S, as found in the previous analysis, a negative size-growth dependence can be generated by a declining size-profile of $g_{\overline{S}}$. In order to investigate the relation between S and $g_{\overline{S}}$, we decompose $g_{\overline{S}}$ making use of the following expression (see Section SM6 for the derivation):

$$g_{\overline{S}} = ln\left(e^{g_{s*}} + R^{in}\kappa^{in} - R^{out}\kappa^{out}e^{g_{s*}}\right) - g_K, \tag{6}$$

where κ^{in}, κ^{out}, R^{in}, R^{out}, and g_{S*} are defined as follows, omitting for simplicity the time subscript t: (i) $\kappa^{in} \equiv K^{in}/K_{-1}$ is the products inflow rate, where K^{in} is the number of new products marketed in the current period that were not observed in the previous period; (ii) $\kappa^{out} \equiv K^{out}/K_{-1}$ is the products

outflow rate, where K^{out} is the number of products marketed in the previous period that are lost in the current period; (iii) $R^{in} \equiv \overline{S}^{in}/\overline{S}_{-1}$ is the ratio between average sales of new ($\overline{S}^{in} = S^{in}/K^{in}$) and existing products ($\overline{S}_{-1} = S_{-1}/K_{-1}$), where S^{in} are the sales generated by new products in the current period; (iv) $R^{out} \equiv \overline{S}^{out}/\overline{S}_{-1}$ is the ratio between average sales of lost ($\overline{S}^{out} = S^{out}/K^{out}$) and existing products, where S^{out} are the sales generated in the previous period by lost products; (v) $g_{s^*} \equiv ln(S^*) - ln(S^{*1})$ is the growth rate of sales generated by stable products, i.e. those products that are observed both in the current and previous period, where $S^* = S - S^{in}$, and $S^{*1} = S_{-1} - S^{out}$[19].

Equation 6 highlights the various channels through which product flows can contribute to $g_{\overline{S}}$ and hence firm growth. We make use of this decomposition to establish a relation between S and the various components of $g_{\overline{S}}$ and hence identify the channels that can lead to a negative size-growth relation. The channels are identified analysing the derivative of $g_{\overline{S}}$ with respect to S, shown in the following equation:

$$g_{\overline{S},S} = \frac{e^{g_{S^*}} g_{S^*,S} \left(1 - R^{out}\kappa^{out}\right) + R^{in}_S\kappa^{in} + \kappa^{in}_S R^{in} - e^{g_{s^*}} \left(R^{out}_S\kappa^{out} + \kappa^{out}_S R^{out}\right)}{e^{g_{s^*}} + R^{in}\kappa^{in} - R^{out}\kappa^{out}e^{g_{s^*}}} - g_{K,S}, \quad (7)$$

where k^{in}_S, k^{out}_S, R^{in}_S, R^{out}_S, $g_{S^*,S}$, and $g_{K,S}$ indicate derivatives with respect to S. From this equation it is clear that a negative relation between $g_{\overline{S}}$ and size ($g_{\overline{S},S} < 0$) can be generated by a declining size-profile of R^{in} ($R^{in}_S < 0$), κ^{in} ($\kappa^{in}_S < 0$), and g_{s^*} ($g_{S^*,S} < 0$), and by an increasing size-profile of R^{out} ($R^{out}_S < 0$) and κ^{out} ($\kappa^{out}_S < 0$).[20] In order to identify candidate explanations for the negative size-growth dependence, we specify statistical models to estimate the five derivatives k^{in}_S, k^{out}_S, R^{in}_S, R^{out}_S, $g_{S^*,S}$, by IV dynamic panel estimators. The derivative $g_{K,S}$ in Equation 7 was already estimated to be equal to zero (see Table 6) and hence is not considered again here.

Table 7 reports FD-GMM estimates without and with correction for attrition of autoregressive models for the following dependent variables: κ^{in}, κ^{out}, R^{in}, R^{out}, and g_{S^*}. κ^{in}, κ^{out}, R^{in}, and R^{out} are expressed in logs, adding 1 to avoid loss of observations associated to zero inflows or outflows. In models for κ^{in} and κ^{out}, the variable $ln(K_{-1})$ is treated as endogenous, while in models for $ln(1 + R^{in})$ and $ln(1 + R^{out})$, the endogenous variables are $ln(1 + R^{in}_{-1})$ and $ln(1 + R^{out}_{-1})$, respectively. For g_{S^*}, $ln(S_{-1})$ is used as an endogenous variable in place of $ln(S^{*1})$ because the two variables are highly collinear. The coefficients associated to $ln(S_{-1})$ in the various models are used to estimate the sign

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[19]Note that S^{*1} does not correspond to the lagged value of S^*, S^*_{-1}. In fact, while S^{*1} represents sales generated in $t-1$ by products that are observed both in t and $t-1$, S^*_{-1} represents sales generated in $t-1$ by products that are observed both in $t-1$ and $t-2$. S^{*1} is equivalent to S^*_{-1} in case of no product flows.

[20]These conclusions are based on the following four results: (i) S, S_{-1}, K^{in}, K^{out}, S^{in}, S^{out}, S^*, S^{*1} are all positive quantities because we are considering firms on the market ($S > 0$, $S_{-1} > 0$) which experience flows in products ($K^{in} > 0$, $K^{out} > 0$), and a product exists so long as it generates positive sales ($S^{in} > 0$, $S^{out} > 0$); moreover S^* and S^{*1} are positive if there exists at least one product observed both in the current and previous period, which is always the case in our sample; (ii) κ^{in}, κ^{out}, R^{in}, R^{out}, $e^{g_{s^*}}$ are positive by definition; (iii) the denominator of Equation 7 is necessarily positive because $e^{g_{s^*}} + R^{in}\kappa^{in} - R^{out}\kappa^{out}e^{g_{s^*}} = S/S_{-1} > 0$; (iv) $(1 - R^{out}\kappa^{out})$ is positive because $(1 - R^{out}\kappa^{out}) = 1 - S^{out}/S_{-1}$, and $S_{-1} - S^{out} = S^{*1} > 0$, where $S^{*1} > 0$ following (i).

of the derivatives.

For κ^{in} and κ^{out}, attrition tests reported in Table 7 provide no evidence of attrition, similarly to results for the growth rate of K (see Table 6), therefore we consider FD-GMM as our best model in these cases. The coefficient of $ln(S_{-1})$ is not significantly different from zero in either cases, suggesting that the inflow rate as well as the outflow rate are not affected by firm size. This evidence is consistent with the previous finding that S has no impact on g_K. FD-GMM is chosen as best model also for R^{in} and R^{out}, because no evidence of attrition is found in these cases either. Note, however, that the attrition test is very close to rejection in both cases. FD-GMM estimates suggest that a 1% increase in size leads to a % reduction in R^{in} of $0.129 \cdot (1 + R^{in})/R^{in}$, and to a % increase in R^{out} of $0.015 \cdot (1 + R^{out})/R^{out}$, which correspond, respectively, to -0.78% and 0.46% if R^{in} and R^{out} are evaluated at sample means (see Table 5). Both effects are statistically significant, however, while the effect on R^{in} is strongly significant, the effect on R^{out} is close to the 5% threshold. Moreover, remark that the effect on R^{out} becomes insignificant if attrition is taken into account, and that the attrition test is very close to rejection ($p = 0.055$). Therefore, the effect on R^{out} appears quite weak overall. Finally, FD-GMM-ATT is used as best model for g_{S*} because the attrition test is strongly significant; this model points out a negative effect of size on g_{S*}. By considering best models in Table 7 altogether, the usual diagnostic tests do not raise any concerns on their validity. These statistics are reported in the Supplemental Material (Section SM5) together with the full set of model estimates (Section SM4), selection regressions (Section SM2) and first-stage results (Section SM3).

To summarize the results in Table 7 on size-effects included in $g_{\overline{S},S}$ (see equation 7), we can conclude that the observed negative size-dependence of firm growth can be accounted for by a declining size-profile of R^{in} and g_{S*}, and by an increasing, although moderately, size-profile of R^{out}. Rates of product flows do not mediate this relation, instead. A declining size-profile of R^{in} means that products launched by smaller firms have larger market impact relatively to the firm existing portfolio, on average. Since larger market impact may be the result of more innovative products, this finding suggests a possible crucial role of innovation in generating the negative dependence. However, a declining size-profile of g_{S*} points out also a channel arising by existing products. In fact, this finding implies that products that are stably observed in two consecutive periods have higher average growth if they are attached to smaller firms. Note that g_{S*} is the net growth rate after removing sales jumps and drops arising by product flows, and that such negative size-dependence was not observed for stable portfolio firms throughout all the investigation period. Therefore, a possible explanation of this finding is that product flows may generate an additional size-penalty via externalities on the existing product portfolio, such as cannibalization effects. Finally, a moderately increasing size-profile of R^{out} indicates that the small firm advantage in the impact of inflows can fade out at some point and even be reversed at the end of the product life cycle.

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Overall, the findings presented in this section show that, while small and large firms grow similarly in the number of products in their portfolio, small firms grow more in sales because the relative size of products they launch generates larger relative changes. In addition to the growth-premium driven by the initial market impact, new products may lead to a size-penalty also generating externalities on the existing firm portfolio that are more detrimental to large firms. In the absence of product flows, these mechanisms cannot operate and the departure from the Gibrat law disappears. Therefore, creation of new products appears a key driver of the departure.

6. Results: Uncovering the role of product innovation in the negative size-growth dependence

This Section presents and discusses evidence on the role of innovation via creation of new products in explaining the documented negative size-growth dependence. Specifically, Section 6.1 investigates the innovative content of new products, while Section 6.2 analyzes their influence on the firm existing portfolio.

6.1. Negative size-dependence in the market impact of new products (R^{in})

In order to ascertain whether small firm products may have larger market impact because they are more innovative, we investigated the innovative profile of new products and its relation with firm size. The focus of the analysis is on product innovation, which, following the OECD Oslo's manual, is defined as a "new or improved good or service that differs significantly from the firm's previous goods or services and that has been introduced on the market" (OECD and Eurostat, 2018). Only new products produced as a result of a technological or knowledge advancement are considered as product innovations, in the sense that they "can use new knowledge or technologies, or be based on new uses or combinations of existing knowledge or technologies" (OECD and Eurostat, 2018). Finally, only new products introducing a novelty on a worldwide scale are considered as product innovations. To summarize, we define new-to-world product innovations (NWPI) as new products possessing the attributes of novelty, advancement, and worldwide scope. The focus on NWPI is motivated by the goal of mitigating the incidence of marketing-oriented innovations and to single out the role of R&D efforts in the influence that innovation may have on the determination of the size-growth dependence.

Table 8 reports shares of innovations for the total sample of 16,852 products that are launched in the reference period. Various types of innovations were identified using criteria based on molecular profile, national market, and brand status. Two definitions of NWPI were specifically employed. Note that the sample used to calculate these shares may become more specific when moving from the top to the bottom of the Table. Table 8 reports also difference-in-means t-tests between small and large

firms, where small firms are defined following the 10 million Euro threshold currently in use by the European Commission (European Commission, 2003).[21]

The first and more restrictive definition of NWPI is based on novelty of molecular entities. On top of Table 8 it is shown that 5.7% new products contain a new molecule for the worldwide market (NMM), and that this share grows to 9.1% if one extend the definition to new molecule combinations, that is combinations of existing molecules that have not been combined in that specific way yet. The two types of innovation are considered together to define the first set of NWPI, i.e. those based on new molecule combinations (NMC), where this definition comprises also NMM. The small-large firm comparison shows that the share of NWPI defined in this way is significantly larger for small firms (11.9% vis-á-vis 7.9%, $t = -8.4$). Therefore, when innovation is defined in a restrictive way, it appears that small firms tend to launch innovative products more often. Moreover, note that the mean-difference is particularly large for the most radical innovations, i.e. NMM (8.3% vis-á-vis 4.4%, $t = -10.19$).

Moving down along Table 8, one can see statistics for the residual sample of new products based on existing molecule combinations (EMC) on the worldwide market. The Table first reports the share of new-to-firm molecules (NMF) and the share of products creating a new market (NMKT). NMF products possess a molecular profile that has not been associated to any products commercialized by the firm beforehand. NMKT products introduce a molecule mix for the first time in at least one national market. Both innovations appear of interest to assess possible overlap between new and existing products in the firm's portfolio. The Table shows that small firms tend to launch NMF products much more often than larger firms (67.3% vis-á-vis 53.3%, $t = -16.32$), but there are no significant differences for NMKT products. The share of NMKT products is reported also for the sub-samples of NMF and EMF products. The difference in the share of NMKT products is not statistically significant for NMF, but small firms have a significantly larger share in the EMF sample, suggesting greater market differentiation and hence reduced overlap with respect to existing products in their portfolio.

A second definition of NWPI is considered by restricting the sample to only EMC-EMKT products. In fact EMC-NMKT products may typically reflect commercial strategies to expand the market of a given product, and hence they may not be the result of genuine innovation efforts. Conversely, EMC-EMKT products are more likely to introduce some more tailored product variation to supply more effectively a market segment already served by existing products. Within the sample of EMC-EMKT products, NWPI are identified by branded (BRN) drugs, as opposite to generic unbranded (UBRN) drugs. Brand-new products based on existing molecular mix may typically introduce modifications to

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[21] Consistently with sales value being expressed in British pounds of 2006q1, the cutoff was converted using the average exchange rate in this trimester, resulting in 6.862 million British pounds.

existing products, such as a new variant of the molecular entity with the potential for improved drug efficacy or reduced side effects, superior formulation to promote patient compliance by reducing daily administration, or new delivery method which can improve adherence or reduce side effects (Hong et al., 2005; Song and Han, 2016). Such novelties might be the result of significant R&D efforts and may generate substantial benefits for some consumers (Kappe, 2014). Conversely, generics are certified drugs bio-equivalent to brand-name medicines that can enter the market when the patents of original drugs expire, and hence do not introduce any product innovation. Generic drugs can be "unbranded generics", when marketed with the chemical name of the molecule, or "branded generics", when the company or a fantasy name is used (Garattini and Tediosi, 2005). Unbranded generics are identified in the present data by comparing the molecule and product name string, while branded drugs are identified residually.[22] Note that the group of branded drugs comprises also branded generics, whose name may differ to molecule's name, and hence cannot be identified in the present data. However, the share of branded generics is very low in many developed countries, notably in the US, the UK, France and Canada, and it decreased in several countries over the 2000's (Danzon and Furukawa, 2011); therefore, such measurement error should influence the comparison only marginally. Table 8 shows that, following this broader definition, the share of NWPI in the EMC-EMKT sample is equal to 46.3%. Such innovations are much more frequent for small firms (56% vis-á-vis 41.9%, $t = -12.84$), suggesting that small firms appear more innovative even when a more lenient definition of NWPI is employed. In order to check for possible measurement error associated to the inclusion of branded generics among EMC-EMKT-BRN innovations, we calculated shares also for a set of very large countries where such drugs are nearly irrelevant, namely USA, UK, France and Canada (Danzon and Furukawa, 2011). Even in this case the divergence between small and larger firms appears substantial (52.4% vis-á-vis 34.5%, $t = -9.27$). Table 8 shows also that small firms have higher NWPI shares for the NMF and EMF sub-samples separately. Evidence of higher innovation intensity in the NMF sample, mostly in comparison with the EMF sample, suggests that the small firm innovation advantage is not primarily driven by product line extensions. Line extensions are a rather common commercial strategy to protect a branded drug whose patent is close to expiry from generics competition by launch of a variant of the lead drug (Ganuza et al., 2009); these products should appear as EMC-EMKT-BRN innovations in the EMF sample.

Table 8 shows overall that the share of NWPI is larger in the sample of small firms, either when innovation is defined in a restrictive (NMC) or in a broader way (EMC-EMKT-BRN). In particular, by considering altogether the two types of innovations, the share of innovative products on the total sample of new products is 42.3% for small firms against 32% for large firms. This difference in the

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[22]Unbranded generics are identified by calculating the Levenshtein distance for any combination of string pairs within the product and molecule names. A product is defined as unbranded generic if there exist at least one string pair with a value of the distance lower than 0.5, where distance is normalized by the length of the longer string.

innovative content of new products may contribute to the larger relative market impact of small firm products and hence to the negative size-growth relation. This hypothesis was tested by estimating the size-dependence of the relative size of new products (R^{in}) inclusive of such innovations only. Table 9 reports estimates of FD-GMM models (with and without attrition correction) for the two proposed definitions of product innovations. The first two columns report estimates for the more substantial innovations (NMC), and the next two columns for the definition that additionally includes new brand drugs commercialized on existing markets (NMC & EMC-EMKT-BRN). Remind that EMC-NMKT and EMC-EMKT-UBRN products are not included in these definitions because they are likely to reflect marketing strategies and hence any possible size-dependence associated to these products would not be driven by genuine product innovation. Results show that the coefficient of size is negative and strongly significant in all models considered, similarly to the baseline definition of R^{in} including all new products. Therefore, since the relative market impact of NWPI is inversely related to firm size, we gather that NWPI contribute to explain the negative size-growth relation. Diagnostics tests for best models in Table 9 are reported in the Supplemental Material (Table SM30), and do not raise concerns on the validity of estimates.

Overall the evidence presented in this Section suggests that smaller firms tend to launch more innovative products and that such innovations contribute to explain the larger market impact of small firm products documented in Section 5.2 and hence the negative size-growth dependence.

6.2. Negative size-dependence in sales growth of stable products (g_{s^*})

This Section analyzes the influence of new products on the firm existing portfolio. The documented declining size-profile of g_{S^*}, where S^* is defined by products that are stably observed in two consecutive periods, suggests that the negative size-growth dependence persists even when the initial impact of inflows is netted out, which was found to be a major driver of such dependence. Such evidence appears in contrast with the Gibrat-like behaviour observed for firms with stable portfolio. Therefore it is possible that product flows generate an additional size-penalty via externalities on the existing portfolio.

In the pharmaceutical sector, a typical externality may be cannibalization by new products. For example, it is rather common for pharmaceutical firms to introduce product line extensions to fend off competition on their branded drugs from generic producers (Hong et al., 2005; Ganuza et al., 2009). This strategy can lead the extending firm to gain higher profits and price-setting power than what would be achieved without the extension (Kadiyali et al., 1998; Kamien and Zang, 1999), however the position of the brand-line in the long-term can be weakened if the share held by the lead product is cannibalized by the extensions (Quelch and Kenny, 1994).

Some findings already presented in Table 8 (Section 6.1) show a significantly higher overlap between new and existing products for larger firms, hinting at possible differential cannibalization effects.

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First, larger firms have significantly lower share of molecule-based (NMC) product innovations (7.9% vis-á-vis 11.9%, $t = -8.4$) and, among products with existing molecule combinations (EMC), a much lower share of new-to-firm molecules (NMF) (53.3% vis-á-vis 67.3%, $t = -16.32$), suggesting higher potential competition with products in the current portfolio. Second, larger firms tend to launch products with in-house molecule profile (EMC-EMF) less often on a new national market (NMKT) (36.2% vis-á-vis 39.6%, $t = -2.33$), possibly exposing a larger share of their existing products to cannibalization. Third, larger firms have a much lower share of branded products among those launched on an existing market with in-house molecule profile (EMF-EMKT) (52.7% vis-á-vis 67.4%, $t = -7.69$), suggesting again lower differentiation. However, note that such findings may also imply greater product replacement rather than sales erosion, whereby only the latter mechanism is relevant for the analysis of stable products.

The relation between firm size and cannibalization effects is tested by decomposing sales of stable products (S^*) between product sales that might be exposed or might not be exposed to cannibalization by new products. Exposure to cannibalization is inferred by the ATC code and the country where the product is sold. Namely, a product is considered potentially cannibalized from a given year t onward if a new product with same ATC code is launched in the same national market in t by the firm owning the product. The ATC code allows extending the scope of potential cannibalization with respect to molecule mix identity, because drugs with different chemical mix but similar therapeutic profile can be also included in the definition. The level of the ATC classification considered for this analysis is the fourth (ATC4), corresponding to the chemical, therapeutic or pharmacological subgroup and identified by the first five digits. Such very fine level is chosen to restrict the sample of potential competitors to very close substitutes, for which cannibalization should be mostly evident.[23] According to these definitions, products exposed to cannibalization account for 25.2% of the entire sales volume and products not exposed account for 37.7%. The residual 37.1% is accounted for by products that either flow in (17%) or out (20.1%) in the reference period, with a share of 7.3% corresponding to products that might cannibalize existing products. Similarly to statistics on firm new molecules (NMF), the share of new products with no ATC-overlap is much larger for small firms (48% vis-á-vis 26.5%, $t = -28$), suggesting greater diversification of small firms also with this definition. We refer to these products as new-to-firm product innovations (NFPI), as opposite to new-to-world product innovations (NWPI) discussed in Section 6.1.

Table 10 reports FD-GMM estimates (with and without attrition correction) of size-growth equations for three definitions of S^*: (i) pooled sales aggregate of products exposed and non-exposed to cannibalization, which is obtained removing sales associated to product inflows and outflows from

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[23]For example, amoxicillin (J01CA04) belongs to the chemical subgroup Penicillins with extended spectrum (J01CA), and hence is assumed substitute for other penicillines such as ampicillin, pivampicillin and others, but not for agents among Beta-lactamase-sensitive penicillins (J01CE), such as benzylpenicillin and others.

the definition used for Table 7, (ii) product sales exposed to cannibalization; (iii) product sales non-exposed to cannibalization. Note that all these definitions are based on products that are consistently observed for the entire period, unlike the definition used in Table 7. The first two columns of Table 10 show a negative effect of firm size on g_{S^*} based on aggregated sales, however the coefficient is not significant in the FD-GMM model without correction for attrition. Since the attrition test provides strong evidence of attrition (for diagnostic tests, see Table SM31 in the Supplemental Material), we conclude that a negative size-growth relation persists even after removing product flow sales. However, note that these effects appear weaker relative to Table SM20, as consistent with the impact of inflows being washed out of the relation. For the cases where S^* amounts to only exposed or non-exposed products, the attrition test is not significant at 5%, therefore FD-GMM models are considered as reference models. Coefficient estimates for firm size show a clear divergence between the two sales components: while a strong negative relation is found for exposed products, the size-dependence disappears for non-exposed ones. Diagnostics tests for best models reported in Table SM31 do not raise significant concerns on the validity of estimates. On the one hand, this evidence suggests that the Gibrat law holds even for firms with variable portfolio if only the stable component of their portfolio is accounted for and sales volumes potentially exposed to cannibalization by new products are netted out. This result is consistent with evidence that the Gibrat law holds for the sample of firms with stable portfolio. On the other hand, this evidence corroborates the role of product innovation as a major driver of the departure from the Gibrat law. In this case, a small firm growth-premium is driven by smaller cannibalization effects as allowed by a higher rate of NFPI. In order to check robustness of these results to the definition of cannibalization, the same analysis was repeated considering the third level of the ATC classification (ATC3). By using ATC3 instead of ATC4, exposure to cannibalization is extended to less closely substitutable products, but still in the same pharmacological or therapeutical class.[24] Results are reported in Table SM21 (see Section SM4 in the Supplementary Material) and show very similar effects to the ones reported in Table 10.

Differences in cannibalization effects between small and large firms are illustrated also graphically by Figure 1. The Figure shows a time-to-event analysis of product sales associated to inflows and to existing products belonging to the same firm and ATC code, both before and after the inflow year. The sample used for calculations comprises all firms launching new products in the same ATC code of their own existing products. Product sales were normalized by subtracting the average sales of products in same year, ATC code and age decile. Normalized product sales were averaged across combinations of firm, year, and ATC code, and for each combination the timeline was re-scaled setting the origin equal to the year of first inflow in the firm-ATC combination. Normalized product sales were then

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[24]According to this definition, amoxicillin (J01CA04) is assumed substitute for other agents within the class J01C (Beta-lactam antibacterials, penicillins) such as Beta-lactamase-sensitive penicillins, Beta-lactamase-resistant penicillins (J01CF) and others, which were not substitutes with the ATC4-level definition.

averaged across periods for inflows and existing products separately. Note that the cohort of inflows has valid values only since period 0 onward, while existing products are exposed to cannibalization only when the latter are observed. Similarly to estimates in Table 10, Figure 1 shows a clear divergence between small and large firms in the relation between new and existing product sales. For large firms, we observe a steep decline in normalized sales of existing products in the post-inflow period, which appears in contrast with the dynamics in the pre-inflow period. Conversely, for small firms there do not appear to be trend discontinuities between the pre- and post-inflow period. It is also interesting to note that the normalized value of inflow product sales is always below the line of existing products for larger firms, and always above for small firm. This evidence suggests that, for this particular type of products, the difference in relative size of inflows between small and large firms documented in Section 5.2 appears to persist even after the first year. Very similar patterns are observed also when the ATC3 classification level is used in place of ATC4, supporting robustness of results (see Figure SM5, Section SM4, in the Supplementary Material).

As a possible explanation for differential cannibalization effects between small and large firms, we investigated the influence of expiry of drug patents. When the patent protection expires, competition from generic manufacturers may cause a sharp decline in sales of the innovator's drug, known as "patent cliff" (Harrison, 2011), which might have perceptible consequences on firm sales, especially for major blockbuster drugs (Song and Han, 2016). Innovator firms often try to mitigate the patent cliff by launching variants of the lead drug near patent expiry, which may result in cannibalization.

The influence of patent expiry was analyzed by using US drug patent expiry dates retrieved from the FDA Orange Book (U.S. Food and Drug Administration, 2019).[25] The US appear a suitable case study because generic competition is particularly fierce in this country, and hence the patent cliff should be clearly detectable. We were able to match to our data 258 US patents with expiry date within the period 1996-2008; the analysis is documented and discussed in details in the Supplemental Material in Section SM1. Two main pieces of evidence can be gathered from this analysis. First, patent expiries are unlikely to influence estimation of the size-growth relation in general. In fact, although a sharp discontinuity can be clearly observed for products soon after expiry of their patent, owner firms experience only a minor deviation from their growth trend, because these drugs account for less than 6% of their sales. Moreover, patent expiries account for a minimal fraction of products present on the US market, suggesting that such deviations should not have any meaningful impact on the US market as a whole. Second, patent expiries do not appear to explain differential cannibalization effects between small and large firms. Larger firms are found to experience lower deviation from their growth trend, but the patent cliff associated to their drugs appear to be milder as well. So, while

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[25]The list was received by the FDA upon formal request.

it is possible that larger firms manage to mitigate the sales cliff through line extensions, there is no evidence that such inflows come with higher cannibalization of the lead drug. In addition, note that any possible influence of patent expiry on differential cannibalization should be quantitatively very modest, because drugs near patent expiry account for a very small share of owning firm, at least for the US case, while the share of sales exposed to cannibalization was estimated to be around one fourth of the entire market.

7. Conclusions

In this paper we investigated the relation between firm size and growth using sales data for a panel of pharmaceutical firms over the period 2002-2008. Existing studies have abundantly documented the prevalence of a negative relation, in contrast with the independence assumption of the popular Gibrat law. However, the literature has dedicated only limited attention to investigate the determinants of this empirical regularity. Taking advantage of the possibility to decompose firm sales by the portfolio of products, the major contribution of the present work was to explore the role of innovation, in particular through product switching, as possible determinant of the departure from Gibrat law. The analysis was performed in three steps. First, we tested the relation between firm size and growth by employing an econometric approach capable to correct simultaneously for endogeneity and firm exit, and found that the typical negative dependence holds even with these corrections.

Second, we compared the samples of firms with flows in the portfolio of products and with invariant portfolio, and found that the negative dependence emerges only in the first sample, while a Gibrat-like behaviour is observed in the second one. This evidence suggests that product inflows and outflows may be a key driver of the departure from the Gibrat law. In order to dig into the influence of product flows, we decomposed the growth rate of firms with variable portfolio by the contribution of product flows and stable products, and studied the relation of the various components with firm size. We found that, while size has no effect on the inflow, outflow, and net flow rate in the number of products K, smaller firms launch new products that generate higher sales relatively to the average sales of their existing portfolio. For a given growth rate of K, higher relative sales of new products determine higher jumps in firm size, hence accounting for a negative dependence between firm size and growth. In addition, a size-penalty was found even in the growth component associated to stable products, obtained after removing product flow sales. This finding points out a violation of the Gibrat law also for the stable component of firms with variable portfolio, in contrast with the Gibrat-like behaviour observed for firms with stable portfolio.

Third, we investigated the role of product innovation as possible mediator of the two identified channels. On the one hand, we identified new-to-world product innovations (NWPI) on the basis of molecule entities, national markets, and brand status, and analyzed their contribution to the

documented size-penalty in the market impact of inflows. Using either a restrictive or a more extensive definition of NWPI, we found that the share of NWPI is significantly larger for small firms, and that the relative market impact of new products is inversely related to firm size even when only such genuine product innovations are considered. This evidence indicates that the innovative profile of small firm new products contributes to explain the negative size-growth relation. On the other hand, we found that small firms have also higher propensity to new-to-firm product innovations (NFPI), pointing out lower risk of cannibalization of existing products. We tested cannibalization effects decomposing sales volumes associated to stable products between products possibly exposed or non-exposed to cannibalization, where exposure was defined by same Anatomical Therapeutic Chemical (ATC) class of any new product. We found a strong negative relation for firm sales associated to exposed products, suggesting that cannibalization effects are stronger for larger firms. Conversely, the size-dependence disappears for non-exposed products, suggesting that the Gibrat law can hold even for firms with variable portfolio if sales are isolated by the influence arising by product flows, either directly or via cannibalization, similarly to firms with stable portfolio.

The present results indicate that product innovations are a key driver of the growth-premium of small firms. This premium is generated either by new-to-world innovations, in the form of larger relative size, or by new-to-firm innovations, in the form of lower cannibalization of existing products. This evidence is in line with the typical division of innovative labour between small and large firms in the pharmaceutical sector, where small firms focus on the more uncertain process of innovation around niche drugs, and large firms on the marketing and distribution of less innovative or imitation drugs (Mazzucato and Dosi, 2006; Demirel and Mazzucato, 2012). More in general, it is coherent with previous studies that emphasized a relative advantage of small firms in conducting innovative activities (see Acs and Audretsch, 1990, 1991, *inter alia*), and in performing product and radical innovations (see Cohen and Klepper, 1996a,b, *inter alia*). The present results contribute also to the literature on firm size and innovation by showing that the observed small firm innovative advantage contributes to the growth differential between small and large firms. Furthermore, these results enrich recent evidence provided by Argente et al. (2019) for the US consumer goods sector, who find that firm growth can only be sustained by continuous addition of new products with sufficiently large market impact. The present results complement this evidence pointing out that such source of growth may taper off as the firm becomes larger.

Our results on the relation between cannibalization and firm size are relevant also for the literature on multi-product firms and international trade. In this context, the risk of cannibalization effects originating by portfolio expansion gives rise to strategic interactions that moderate firms reaction to trade liberalization, with consequences on firm productivity, factor prices, and product variety (Eckel and Neary, 2010; Feenstra and Ma, 2008). Evidence of a size-penalty in cannibalization may

suggest that smaller firms are in a better position to internalize demand linkages between products in their portfolio and to invest in product differentiation, possibly generating higher benefits in case of exposure to open competition. We are not aware of any prior econometric study investigating the relation between cannibalization and firm size.

The results of our analysis have clear policy implications. First, the finding that small firms have higher growth rates than larger firms is often used to strengthen the case for policy support to small firms. However, since previous studies reporting a negative size-growth relation did not investigate the drivers of such dependence, they were unable to pinpoint the most efficient policy tool to spur small firms growth. By uncovering the role of innovation in generating the small firm growth premium, our results suggest that support to small firms should prioritize innovation policies. This policy receipt is consistent with a body of evidence reporting that R&D tax incentives are more effective for smaller firms (Sterlacchini and Venturini, 2019; Castellacci and Lie, 2015; Appelt et al., 2016). Furthermore it bears support to the policy orientation of the European Commission, which allocates a significant budget to enhance the innovation capacity of small firms.

As a second policy implication, the present analysis points out the importance of the measuring approach to innovation. The launch of new products has been considered by previous literature as a more suitable measure of innovation than alternative options (Kleinknecht et al., 2002; Hagedoorn and Cloodt, 2003; Corsino and Gabriele, 2010), however only few studies analysing the size-growth relation were able to use this information. Furthermore, to our knowledge, there are no studies that have investigated the relation between firm size and innovative performance via the market impact of new products or via cannibalization. As concerns the first measure of innovative performance, evidence of a small firm proportional advantage in the impact of new products, rather than in the portfolio growth, points out that omitting to take into account the market impact of innovations may result in misleading conclusions about the relationship between firm size and innovative performance. As concerns the second measure, failure to take into account externalities generated by new products on the firm portfolio may lead to underestimate the small-firm advantage in innovation performance. Therefore we recommend that innovation policies take into consideration, beyond the usual support to R&D investment (Colombelli et al., 2013), also the output of innovations as well as their possible cannibalization effects.

Finally, one has to bear in mind that results and implications of the present study are derived from the analysis of a specific industrial sector, therefore their validity might depend on characteristics that are specific to that industry. For example, a relative innovative advantage of small firms has been traditionally linked to markets characterized by an entrepreneurial technological regime, where innovations tend to come from knowledge that is not of a routine nature, as opposite to a routinized technological regime, where large firms have an innovative advantage (see Audretsch and Fritsch,

2002, and references therein). An entrepreneurial regime seems to prevail in industries that are highly innovative (Acs and Audretsch, 1990) such as the pharmaceutical sector, therefore the results of the present analysis might reflect the specific technological regime of this sector. Moreover, a relative innovative advantage of small firms has been also associated to industries where innovations are more saleable in disembodied form or prospects for rapid growth due to innovation are greater, which seems to be the case of the pharmaceutical industry (Cohen and Klepper, 1996b). Future research might investigate whether the small firm innovative premium found in our analysis applies to other industrial contexts.

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Tables and Figures

Table 1: Summary statistics for the estimation sample. Means and standard deviations

	Total	2002	2003	2004	2005	2006	2007	2008
S (millions)	105.1	89.8	93.8	101.0	107.5	111.0	112.8	117.3
	(837.0)	(726.0)	(765.8)	(821.2)	(863.0)	(874.0)	(880.8)	(899.6)
g_S (%)	-5.5	-8.3	-4.4	-7.6	-3.7	-8.0	-4.4	-2.2
	(43.3)	(45.4)	(43.3)	(44.6)	(40.4)	(41.1)	(43.3)	(44.6)
K	33.4	36.7	35.0	34.3	32.9	32.5	31.8	31.1
	(100.9)	(110.1)	(105.0)	(102.6)	(99.3)	(97.6)	(96.7)	(95.2)
g_K (%)	-1.6	0.9	-2.1	-1.9	-2.7	-2.7	-1.6	-1.2
	(19.5)	(18.5)	(22.7)	(18.2)	(19.6)	(20.2)	(18.9)	(18.0)
k^{in} (%)	5.8	7.5	6.6	5.0	5.2	5.4	5.2	5.5
	(20.8)	(19.8)	(36.0)	(13.2)	(17.1)	(17.4)	(17.8)	(16.6)
k^{out} (%)	5.5	4.8	6.0	5.4	6.0	6.2	5.1	5.0
	(11.1)	(9.9)	(11.9)	(10.6)	(11.9)	(12.0)	(10.9)	(10.4)
R^{in} (%)	16.8	19.1	20.6	17.8	16.4	14.1	15.5	14.5
	(90.3)	(99.6)	(110.1)	(86.8)	(87.6)	(107.4)	(68.2)	(64.2)
R^{out} (%)	2.8	1.9	2.1	4.5	2.5	4.4	2.1	2.1
	(24.9)	(12.6)	(12.6)	(50.7)	(18.1)	(28.8)	(13.5)	(12.7)
g_{S^*} (%)	-6.4	-10.1	-6.0	-8.3	-4.6	-7.6	-5.3	-3.3
	(41.9)	(43.2)	(41.5)	(43.1)	(38.9)	(38.9)	(43.2)	(44.1)
S/K (millions)	1.5	0.9	1.3	1.4	1.6	1.8	1.7	1.8
	(16.8)	(6.7)	(14.5)	(16.3)	(19.1)	(21.6)	(17.2)	(17.7)
Age	34.8	34.6	34.2	34.5	34.7	35.2	35.2	35.1
	(23.4)	(22.5)	(22.9)	(23.1)	(23.4)	(23.6)	(23.9)	(24.1)
$newmol$ (%)	25.5	29.0	26.4	26.5	26.1	25.1	23.8	21.9
	(43.6)	(45.4)	(44.1)	(44.1)	(43.9)	(43.4)	(42.6)	(41.3)
$atcmain$ (%)	65.1	63.5	63.8	64.3	65.1	65.6	66.3	67.0
	(29.8)	(30.0)	(29.9)	(29.8)	(29.9)	(29.9)	(29.8)	(29.6)
$atcd$ (%)	11.0	11.9	12.2	11.0	10.6	10.7	10.6	10.3
	(31.4)	(32.4)	(32.8)	(31.3)	(30.8)	(30.9)	(30.8)	(30.5)
Attrition (%)	1.8	2.1	2.7	1.6	2.7	1.8	1.6	0.0
	(13.2)	(14.5)	(16.2)	(12.6)	(16.2)	(13.4)	(12.7)	(0.0)
Obs.	12860	1724	1790	1805	1845	1852	1900	1944

Notes: $S \equiv$ sales; $g_S \equiv ln(S) - ln(S_{-1})$; $K \equiv$ number of products; $g_K \equiv ln(K) - ln(K_{-1})$; $\kappa^{in} \equiv K^{in}/K_{-1}$, where K^{in} is the number of new products; $\kappa^{out} \equiv K^{out}/K_{-1}$, where K^{out} is the number of products lost; $R^{in} \equiv \overline{S}^{in}/\overline{S}_{-1}$, where $\overline{S}^{in} \equiv S^{in}/K^{in}$, S^{in} are the sales generated by new products, and $\overline{S}_{-1} \equiv S_{-1}/K_{-1}$; $R^{out} \equiv \overline{S}^{out}/\overline{S}_{-1}$, where $\overline{S}^{out} = S^{out}/K^{out}$, and S^{out} are the sales generated by products lost; $g_{s*} \equiv ln(S^*) - ln(S^{*1})$ is the growth rate of sales generated by stable products, i.e. products observed both in the current and previous period; $newmol$ identifies firms launching new products with new-to-the-firm molecule; $atcmain$ is the share of sales generated by the main ATC code; $atcd$ identifies firms with a change in the main ATC code.

Table 2: Size-Growth regressions

	OLS	FE	FD-2S	FD-GMM	FD-2S-ATT	FD-GMM-ATT
$ln(S_{-1})$	1.0238**	0.7984**	0.8237**	0.8615**	0.7127**	0.7345**
	(0.0017)	(0.0133)	(0.0491)	(0.0439)	(0.0540)	(0.0523)
$Age = 11 - 20$	−0.0119	−0.0615*	−0.0883**	−0.0877**	−0.0790**	−0.0786**
	(0.0151)	(0.0264)	(0.0295)	(0.0294)	(0.0290)	(0.0294)
$Age = 21 - 50$	0.0021	−0.0585	−0.0996*	−0.0951*	−0.0904	−0.0877
	(0.0136)	(0.0399)	(0.0483)	(0.0481)	(0.0473)	(0.0476)
$Age > 50$	−0.0336*	−0.0206	−0.0944	−0.0901	−0.0898	−0.0874
	(0.0142)	(0.0468)	(0.0551)	(0.0550)	(0.0536)	(0.0542)
k^{in} (%)	0.0016**	0.0010**	0.0010**	0.0011**	0.0010**	0.0010**
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
k^{in}_{-1} (%)	0.0013**	0.0008*	0.0008*	0.0008*	0.0007*	0.0008*
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
k^{out} (%)	−0.0063**	−0.0032**	−0.0025**	−0.0024**	−0.0029**	−0.0029**
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$newmol$	0.0322**	0.0296**	0.0285**	0.0282**	0.0301**	0.0299**
	(0.0110)	(0.0107)	(0.0101)	(0.0101)	(0.0098)	(0.0099)
$newmol_{-1}$	0.0552**	0.0662**	0.0567**	0.0546**	0.0609**	0.0597**
	(0.0111)	(0.0116)	(0.0106)	(0.0105)	(0.0103)	(0.0103)
$newmol_{-2}$	0.0138	0.0293**	0.0309**	0.0290**	0.0361**	0.0348**
	(0.0081)	(0.0093)	(0.0085)	(0.0084)	(0.0082)	(0.0081)
$ln(atcmain)_{-1}$	0.0064	−0.0767**	−0.1411**	−0.1448**	−0.1243**	−0.1271**
	(0.0073)	(0.0261)	(0.0358)	(0.0357)	(0.0333)	(0.0343)
$atcd_{-1}$	0.0416**	0.0269*	0.0353**	0.0332*	0.0307*	0.0294*
	(0.0128)	(0.0132)	(0.0131)	(0.0130)	(0.0120)	(0.0123)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	No	No	No	Yes	Yes
Obs.	12860	12860	12860	12860	12860	12860
Firms	2173	2173	2173	2173	2173	2173

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(S_{-1})$ is instrumented with the following IVs: $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$, $\Delta ln(S_{-4})$. The reported coefficient on $ln(S_{-1})$ is $\tilde{\beta}$; $\tilde{\beta} \neq 1$ corresponds to $\beta \neq 0$.

Table 3: Diagnostic tests of FD-GMM-ATT estimates of size-growth equations (see Table 2)

		Excluded Instruments (3): $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$, $\Delta ln(S_{-4})$
1	Attrition:	$\chi^2(7) = 58.7$ ($p = 0.000$)
2	Autocorrelation	
	AR(1):	$z = -6.6$ ($p = 0.000$)
	AR(2):	$z = -1.1$ ($p = 0.257$)
	AR(3):	$z = -1.3$ ($p = 0.19$)
3	IVs relevance (1st stage):	$F(3, 2172) = 113.7$ ($p = 0.000$)
4	IVs underidentification (all)	$\chi^2(3) = 184.2$ ($p = 0.000$)
5	IVs underidentification	
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) = 151.5$ ($p = 0.000$)
	IV: $\Delta ln(S_{-3})$	$\chi^2(1) = 21.7$ ($p = 0.000$)
	IV: $\Delta ln(S_{-4})$	$\chi^2(1) = 6$ ($p = 0.015$)
6	IVs overidentification (all)	$\chi^2(2) = 1.9$ ($p = 0.383$)
7	IVs overidentification	
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) = 0.8$ ($p = 0.384$)
	IV: $\Delta ln(S_{-3})$	$\chi^2(1) = 0.000$ ($p = 0.991$)
	IV: $\Delta ln(S_{-4})$	$\chi^2(1) = 1.9$ ($p = 0.169$)

Notes:

1. Joint test of the null hypothesis that $\rho_t = 0$, $\forall t$, in Equation 5. Rejection confirms the presence of attrition (Wooldridge, 2010).
2. Arellano-Bond autocorrelation test (AR). In order to test AR in the $u_{i,t}$, the test considers the first-differenced residuals $u^*_{i,t}$. In fact, AR(1) is expected in first differences if $u_{i,t}$ are actually uncorrelated, so to check for AR(1) in levels, one must look at AR(2) in differences (Arellano and Bond, 1991).
3. Test of the null hypothesis that the excluded instruments are jointly non-significant in the 1st-stage equation. Rejection confirms that they are relevant.
4. The IVs underidentification test is an LM test of whether the excluded instruments are redundant, *i.e.* not correlated with the endogenous regressor. Under the null hypothesis that the first-stage equation is underidentified, the matrix of reduced form coefficients on the L excluded instruments has rank=K-1 where K=number of endogenous regressors. Under the null, the statistic is distributed as χ^2 with degrees of freedom=(L-K+1). A rejection of the null indicates that the matrix is full column rank, i.e., the model is identified.
5. Excluded instruments are individually redundant if the asymptotic efficiency of estimation is not improved by using them. Rejection of the null indicates that the instrument is not redundant and hence it is a valid predictor of the endogenous variable.
6. The IVs overidentification test is the Sargan-Hansen statistic testing exogeneity of instruments. Under the null hypothesis the instruments are jointly valid, i.e., uncorrelated with the error term, and correctly excluded from the estimated equation. Under the null, the test statistic is distributed as a χ^2 in the number of (L-K) overidentifying restrictions.
7. The tests report the Difference-in-Sargan C statistic testing the validity of individual instruments. The statistic is computed as the difference of the Sargan-Hansen statistic of the equation with the smaller set of instruments and the equation with the full set of instruments, i.e., including the instrument whose validity is tested. Under the null hypothesis that the smaller set of instruments as well as the tested instrument are valid, the C statistic is distributed as a χ^2 in the number of instruments tested. Failure to reject the null suggests that the IV is valid.

Table 4: Size-Growth regressions. Firms with and without product flows

	Stable portfolio				Variable portfolio			
	FD-2S	FD-2S-ATT	FD-GMM	FD-GMM-ATT	FD-2S	FD-2S-ATT	FD-GMM	FD-GMM-ATT
$ln(S_{-1})$	1.0847**	0.9218***	1.0736**	0.9038**	0.7545**	0.6547**	0.8021**	0.6852**
	(0.1604)	(0.1485)	(0.1449)	(0.1421)	(0.0510)	(0.0596)	(0.0462)	(0.0601)
$Age = 11-20$	-0.1031	-0.1103	-0.1103	-0.1169	-0.0741*	-0.0622*	-0.0761*	-0.0636*
	(0.0712)	(0.0683)	(0.0699)	(0.0656)	(0.0320)	(0.0314)	(0.0320)	(0.0322)
$Age = 21-50$	-0.1589	-0.1759	-0.1660	-0.1821	-0.0768	-0.0645	-0.0729	-0.0617
	(0.1221)	(0.1104)	(0.1214)	(0.1095)	(0.0519)	(0.0502)	(0.0519)	(0.0512)
$Age > 50$	0.0560	0.0176	0.0471	0.0085	-0.0906	-0.0795	-0.0876	-0.0776
	(0.1735)	(0.1649)	(0.1724)	(0.1597)	(0.0584)	(0.0569)	(0.0584)	(0.0582)
k^{in} (%)					0.0010**	0.0009**	0.0010**	0.0009**
					(0.0003)	(0.0003)	(0.0003)	(0.0004)
k^{in}_{-1} (%)					0.0008*	0.0007*	0.0008**	0.0008*
					(0.0003)	(0.0003)	(0.0003)	(0.0003)
k^{out} (%)					-0.0026**	-0.0030**	-0.0024**	-0.0029**
					(0.0005)	(0.0005)	(0.0005)	(0.0005)
$newmol$					0.0292**	0.0304**	0.0289**	0.0302**
					(0.0099)	(0.0096)	(0.0099)	(0.0098)
$newmol_{-1}$					0.0593**	0.0629**	0.0566**	0.0611**
					(0.0104)	(0.0103)	(0.0103)	(0.0103)
$newmol_{-2}$					0.0346**	0.0391**	0.0321**	0.0373**
					(0.0083)	(0.0082)	(0.0082)	(0.0083)
$ln(atcmain)_{-1}$	-0.5699	-0.4597	-0.5505	-0.4344	-0.1374**	-0.1210**	-0.1416**	-0.1244**
	(0.3384)	(0.2874)	(0.3308)	(0.2926)	(0.0344)	(0.0324)	(0.0343)	(0.0340)
$atcd_{-1}$					0.0336**	0.0291*	0.0314*	0.0277*
					(0.0125)	(0.0117)	(0.0125)	(0.0123)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	2026	2026	2026	2026	10834	10834	10834	10834
Firms	440	440	440	440	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(S_{-1})$ is instrumented with the following IVs: $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$, $\Delta ln(S_{-4})$. The reported coefficient on $ln(S_{-1})$ is $\hat{\beta}$; $\tilde{\hat{\beta}} \neq 1$ corresponds to $\beta \neq 0$.

Table 5: Summary statistics for estimation samples. Means and standard deviations

	Full sample		Stable portfolio		Variable portfolio	
S (millions)	105.1	(837.0)	1.4	(8.0)	124.5	(910.6)
g_S (%)	-5.5	(43.3)	-14.4	(53.3)	-3.8	(40.9)
K	33.4	(100.9)	1.5	(1.6)	39.4	(108.8)
g_K (%)	-1.6	(19.5)	0.0	(0.0)	-2.0	(21.3)
k^{in} (%)	5.8	(20.8)	0.0	(0.0)	6.8	(22.5)
k^{out} (%)	5.5	(11.1)	0.0	(0.0)	6.5	(11.8)
R^{in} (%)	16.8	(90.3)	0.0	(0.0)	19.9	(98.0)
R^{out} (%)	2.8	(24.9)	0.0	(0.0)	3.3	(27.1)
g_{S^*} (%)	-6.4	(41.9)	-14.3	(53.3)	-4.9	(39.3)
S/K (millions)	1.5	(16.8)	1.1	(6.5)	1.6	(18.1)
Age	34.8	(23.4)	21.1	(15.5)	37.3	(23.7)
$newmol$ (%)	25.5	(43.6)	0.0	(0.0)	30.2	(45.9)
$atcmain$ (%)	65.1	(29.8)	94.9	(13.3)	59.6	(28.8)
$atcd$ (%)	11.0	(31.4)	1.7	(13.0)	12.8	(33.4)
Attrition (%)	1.8	(13.2)	4.9	(21.7)	1.2	(10.8)
Nr. firms	2173		440		1733	
Obs.	12860		2026		10834	

Notes: See notes to Table 1

Table 6: Size-Growth regressions. Sample of firms with variable portfolio. Dependent variable is $ln(K)$

	OLS	FE	FD-2S	FD-GMM	FD-2S-ATT	FD-GMM-ATT
$ln(S_{-1})$	0.0190**	0.0851**	0.0274	0.0160	0.0245	0.0129
	(0.0011)	(0.0066)	(0.0229)	(0.0217)	(0.0248)	(0.0237)
$ln(K_{-1})$	0.9436**	0.6252**	0.6949**	0.7475**	0.7264**	0.7826**
	(0.0029)	(0.0146)	(0.1185)	(0.1133)	(0.1346)	(0.1312)
$Age = 11-20$	−0.0242**	0.0196	−0.0020	−0.0040	−0.0043	−0.0067
	(0.0088)	(0.0140)	(0.0170)	(0.0170)	(0.0177)	(0.0180)
$Age = 21-50$	−0.0428**	0.0295	0.0191	0.0165	0.0162	0.0130
	(0.0080)	(0.0223)	(0.0260)	(0.0259)	(0.0266)	(0.0265)
$Age > 50$	−0.0570**	0.0378	0.0136	0.0097	0.0119	0.0076
	(0.0081)	(0.0266)	(0.0294)	(0.0292)	(0.0300)	(0.0300)
$newmol_{-1}$	0.0465**	0.0249**	−0.0703**	−0.0773**	−0.0744**	−0.0819**
	(0.0044)	(0.0047)	(0.0164)	(0.0157)	(0.0184)	(0.0181)
$newmol_{-2}$	0.0197**	0.0074	−0.0450**	−0.0492**	−0.0481**	−0.0527**
	(0.0046)	(0.0052)	(0.0114)	(0.0110)	(0.0127)	(0.0126)
$newmol_{-3}$	0.0092*	0.0076	−0.0148*	−0.0163**	−0.0161*	−0.0178**
	(0.0046)	(0.0048)	(0.0063)	(0.0062)	(0.0069)	(0.0069)
$ln(atcmain)_{-1}$	−0.0531**	−0.1130**	0.0228	0.0310	0.0281	0.0370
	(0.0044)	(0.0144)	(0.0316)	(0.0312)	(0.0347)	(0.0354)
$atcd_{-1}$	−0.0445**	−0.0309**	−0.0135*	−0.0125*	−0.0134*	−0.0123
	(0.0068)	(0.0066)	(0.0063)	(0.0063)	(0.0064)	(0.0064)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	No	No	No	Yes	Yes
Obs.	10834	10834	10834	10834	10834	10834
Firms	1733	1733	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(K_{-1})$ is instrumented with the following IVs: $\Delta ln(K_{-3})$, $\Delta ln(K_{-4})$ $\Delta ln(S_{-2})$.

Table 7: Effect of firm size (S) on growth components. Sample of firms with variable portfolio.

dep. var.	$ln(1+k^{in})$ FD-GMM	$ln(1+k^{in})$ FD-GMM-ATT	$ln(1+k^{out})$ FD-GMM	$ln(1+k^{out})$ FD-GMM-ATT	$ln(1+R^{in})$ FD-GMM	$ln(1+R^{in})$ FD-GMM-ATT	$ln(1+R^{out})$ FD-GMM	$ln(1+R^{out})$ FD-GMM-ATT	g_{s*} FD-GMM	g_{s*} FD-GMM-ATT
$ln(S_{-1})$	−0.0119 (0.0103)	−0.0109 (0.0107)	−0.0093 (0.0161)	−0.0069 (0.0172)	−0.1288** (0.0133)	−0.1307** (0.0134)	0.0148* (0.0074)	0.0133 (0.0074)	−0.2006** (0.0511)	−0.3301** (0.0550)
$ln(K_{-1})$	−0.0405 (0.0548)	−0.0469 (0.0602)	0.0541 (0.1028)	0.0264 (0.1145)	0.0875** (0.0233)	0.0750** (0.0237)	−0.0185 (0.0101)	−0.0256* (0.0100)		
$ln(1+R^{in}_{-1})$					−0.0015 (0.0294)	−0.0022 (0.0294)				
$ln(1+R^{out}_{-1})$							−0.0053 (0.0246)	−0.0055 (0.0248)		
$Age = 11 - 20$	−0.0125 (0.0123)	−0.0119 (0.0125)	−0.0035 (0.0092)	−0.0008 (0.0098)	−0.0082 (0.0197)	−0.0063 (0.0197)	0.0099 (0.0114)	0.0115 (0.0112)	−0.0645* (0.0318)	−0.0510 (0.0318)
$Age = 21 - 50$	−0.0026 (0.0165)	−0.0030 (0.0166)	−0.0111 (0.0149)	−0.0086 (0.0153)	−0.0039 (0.0332)	−0.0016 (0.0331)	0.0115 (0.0149)	0.0134 (0.0146)	−0.0636 (0.0527)	−0.0496 (0.0509)
$Age > 50$	−0.0036 (0.0194)	−0.0040 (0.0194)	−0.0126 (0.0163)	−0.0114 (0.0167)	−0.0076 (0.0432)	−0.0067 (0.0431)	0.0082 (0.0180)	0.0086 (0.0178)	−0.0760 (0.0592)	−0.0658 (0.0573)
k^{in} (%)					0.0007* (0.0003)	0.0007* (0.0003)	−0.0000 (0.0000)	−0.0000 (0.0000)	−0.0004* (0.0002)	−0.0005* (0.0002)
k^{in}_{-1} (%)					0.0000 (0.0003)	0.0003 (0.0003)	0.0000 (0.0001)	0.0001 (0.0001)	0.0009* (0.0004)	0.0009* (0.0004)
k^{out} (%)					−0.0005 (0.0003)	−0.0006* (0.0003)	0.0033** (0.0002)	0.0033** (0.0002)	0.0009 (0.0006)	0.0001 (0.0005)
$newmol_{-1}$	−0.0961** (0.0088)	−0.0953** (0.0094)	−0.0051 (0.0132)	−0.0014 (0.0147)	0.0044 (0.0102)	0.0055 (0.0102)	−0.0019 (0.0029)	−0.0014 (0.0029)	0.0520** (0.0117)	0.0553** (0.0113)
$newmol_{-2}$	−0.0602** (0.0062)	−0.0598** (0.0066)	−0.0021 (0.0092)	0.0005 (0.0102)	0.0049 (0.0092)	0.0056 (0.0092)	−0.0007 (0.0036)	−0.0004 (0.0036)	0.0337** (0.0091)	0.0377** (0.0088)
$newmol_{-3}$	−0.0242** (0.0036)	−0.0239** (0.0037)	−0.0035 (0.0046)	−0.0024 (0.0050)						
$newmol$	0.0556** (0.0169)	0.0538** (0.0176)	−0.0001 (0.0257)	−0.0047 (0.0279)	0.1728** (0.0123)	0.1731** (0.0123)	−0.0020 (0.0031)	−0.0019 (0.0031)	−0.0053 (0.0091)	−0.0044 (0.0089)
$ln(atcmain)_{-1}$	−0.0058 (0.0034)	−0.0058 (0.0034)	0.0030 (0.0032)	0.0028 (0.0032)	0.1299** (0.0395)	0.1306** (0.0394)	−0.1014** (0.0148)	−0.1004** (0.0147)	−0.2568** (0.0363)	−0.2310** (0.0343)
$atcd_{-1}$					−0.0483** (0.0116)	−0.0484** (0.0116)	−0.0096 (0.0055)	−0.0095 (0.0055)	0.0447** (0.0130)	0.0404** (0.0121)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Attrition test $\chi^2(7)$		5.1 (0.642)		4.5 (0.715)		13.6 (0.06)		13.8 (0.055)		52.5 (0.000)
Obs.	10834	10834	10834	10834	10834	10834	10834	10834	10834	10834
Firms	1733	1733	1733	1733	1733	1733	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications, otherwise they are firm-clustered robust. In models for k^{in}, the variable $ln(K_{-1})$ is instrumented with the following IVs: $\Delta ln(K_{-3})$, $\Delta ln(K_{-4})$ $\Delta ln(S_{-2})$. In models for k^{out}, the variable $ln(K_{-1})$ is instrumented with the following IVs: $\Delta ln(K_{-3})$. In models for R^{in}, the variable $ln(1+R^{in}_{-1})$ is instrumented with the following IVs: $\Delta ln(1+R^{in}_{-2})$, $\Delta ln(1+R^{in}_{-3})$. In models for R^{out}, the variable $ln(1+R^{out}_{-1})$ is instrumented with the following IVs: $\Delta ln(1+R^{out}_{-2})$, $\Delta ln(1+R^{out}_{-3})$. In models for g_{s*}, the variable $ln(S_{-1})$ is instrumented with the following IVs: $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$.

Table 8: Innovative content of new products and small/large firm comparison. Small/large firms identified by 10 million Euro sales cutoff (NM, EM: new/existing molecule; NMC, EMC: new/existing molecule combination; NMKT, EMKT: new/existing market; NMF, EMF: firm new/existing molecule; BRN, UBRN: branded/unbranded ; n.i.: not included in computation).

							EM					NM
							EMC					NMC
						NMKT		EMKT				
	Count	Mean			t-test	EMF	NMF	EMF		NMF		
		All firms	Large	Small				UBRN	BRN	UBRN	BRN	
Total products	16852					✓	✓	✓	✓	✓	✓	✓ ✓
Small firm	5409	0.321				✓	✓	✓	✓	✓	✓	✓ ✓
NMM	958	0.057	0.044	0.083	-10.19							✓
NMC	1541	0.091	0.079	0.119	-8.40							✓ ✓
Only EMC												
NMF	8827	0.577	0.533	0.673	-16.32		✓			✓	✓	n.i. n.i.
NMKT	5159	0.352	0.349	0.357	-0.88	✓	✓					n.i. n.i.
NMKT (NMF)	2946	0.339	0.339	0.339	0.00	n.i.	✓	n.i.	n.i.			n.i. n.i.
NMKT (EMF)	2213	0.370	0.362	0.396	-2.33	✓	n.i.			n.i.	n.i.	n.i. n.i.
Only EMC-EMKT												
Branded	4405	0.463	0.419	0.560	-12.84	n.i.	n.i.		✓		✓	n.i. n.i.
Branded (NMF)	2288	0.398	0.333	0.513	-13.57	n.i.	n.i.	n.i.	n.i.		✓	n.i. n.i.
Branded (EMF)	2117	0.561	0.527	0.674	-7.69	n.i.	n.i.		✓	n.i.	n.i.	n.i. n.i.

Table 9: Relation between firm size (S) and average sales ratio (R^{in}). Sample of firms with variable portfolio. Dependent variable is $ln(1+R^{in})$, where R^{in} is defined by innovative products with varying innovation extent: NMC, EMC: new/existing molecule combination; NMKT, EMKT: new/existing market; BRN, UBRN: branded/unbranded

	NMC		NMC & EMC-EMKT-BRN	
	FD-GMM	FD-GMM-ATT	FD-GMM	FD-GMM-ATT
$ln(1+R^{in}_{-1})$	−0.0253	−0.0253	−0.0313	−0.0314
	(0.0340)	(0.0340)	(0.0265)	(0.0264)
$ln(S_{-1})$	−0.0216**	−0.0219**	−0.0545**	−0.0555**
	(0.0048)	(0.0049)	(0.0076)	(0.0076)
$ln(K_{-1})$	0.0118	0.0102	0.0032	−0.0021
	(0.0104)	(0.0107)	(0.0188)	(0.0195)
$Age = 11-20$	0.0138	0.0140	−0.0073	−0.0064
	(0.0105)	(0.0104)	(0.0133)	(0.0134)
$Age = 21-50$	0.0156	0.0157	0.0144	0.0151
	(0.0166)	(0.0166)	(0.0254)	(0.0254)
$Age > 50$	0.0088	0.0087	−0.0088	−0.0085
	(0.0227)	(0.0227)	(0.0360)	(0.0360)
k^{in} (%)	0.0003**	0.0002**	0.0007**	0.0007**
	(0.0001)	(0.0001)	(0.0003)	(0.0003)
k^{in}_{-1} (%)	−0.0000	−0.0000	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
k^{out} (%)	0.0000	−0.0000	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
$ln(atcmain)_{-1}$	0.0380*	0.0382*	0.0596	0.0598
	(0.0163)	(0.0163)	(0.0326)	(0.0325)
$atcd_{-1}$	−0.0130*	−0.0131*	−0.0353**	−0.0354**
	(0.0062)	(0.0062)	(0.0106)	(0.0106)
Year FE	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes
Obs.	10834	10834	10834	10834
Firms	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. The endogenous variable is instrumented with $\Delta ln(1+R^{in}_{-2})$, $\Delta ln(1+R^{in}_{-3})$ in all cases. See Table SM30 for diagnostics test.

Table 10: Relation between firm size (S) and sales growth rate of stable products (observed in all periods). Sample of firms with variable portfolio. Dependent variable is g_{S^*}, where product flows have been removed from S^*. S^* is also decomposed between products exposed and non-exposed to cannibalization. Exposure is defined by same ATC4

	Exposed & non-exposed		Exposed		Non-exposed	
	FD-GMM	FD-GMM-ATT	FD-GMM	FD-GMM-ATT	FD-GMM	FD-GMM-ATT
$ln(S_{-1})$	−0.1315	−0.2101*	−0.5782**	−0.5769**	−0.0210	−0.0890
	(0.0877)	(0.1025)	(0.1747)	(0.1767)	(0.0889)	(0.1048)
$Age = 11-20$	−0.0376	−0.0309	0.0511	0.0530	−0.0744	−0.0674
	(0.0574)	(0.0567)	(0.1043)	(0.1046)	(0.0500)	(0.0492)
$Age = 21-50$	−0.0087	−0.0028	0.0169	0.0178	−0.0257	−0.0200
	(0.0701)	(0.0692)	(0.1308)	(0.1318)	(0.0658)	(0.0644)
$Age > 50$	−0.0399	−0.0355	0.0511	0.0474	−0.0579	−0.0526
	(0.0761)	(0.0752)	(0.1398)	(0.1413)	(0.0726)	(0.0712)
k^{in} (%)	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0002)	(0.0002)	(0.0006)	(0.0006)	(0.0002)	(0.0002)
k^{in}_{-1} (%)	−0.0002	−0.0003	−0.0004	−0.0004	−0.0003	−0.0004
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0002)
k^{out} (%)	−0.0006	−0.0012*	0.0017	0.0012	−0.0011	−0.0016*
	(0.0006)	(0.0006)	(0.0016)	(0.0017)	(0.0006)	(0.0006)
$newmol$	0.0220	0.0228	0.0197	0.0203	0.0236*	0.0242*
	(0.0142)	(0.0141)	(0.0221)	(0.0221)	(0.0120)	(0.0118)
$newmol_{-1}$	0.0187	0.0212	0.0269	0.0267	0.0142	0.0171
	(0.0153)	(0.0153)	(0.0221)	(0.0222)	(0.0148)	(0.0148)
$newmol_{-2}$	0.0317*	0.0350*	0.0226	0.0222	0.0239	0.0270*
	(0.0141)	(0.0141)	(0.0233)	(0.0234)	(0.0133)	(0.0133)
$ln(atcmain)_{-1}$	−0.0897	−0.0754	0.0693	0.0691	−0.0705	−0.0604
	(0.0473)	(0.0464)	(0.0766)	(0.0765)	(0.0486)	(0.0476)
$atcd_{-1}$	0.0374*	0.0347*	0.0268	0.0270	0.0412*	0.0385*
	(0.0172)	(0.0169)	(0.0261)	(0.0261)	(0.0163)	(0.0161)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes	No	Yes
Obs.	9984	9984	4537	4537	9556	9556
Firms	1534	1534	656	656	1469	1469

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. The endogenous variable is instrumented with $\Delta ln(S_{-2})$ in all cases. See Table SM31 for diagnostics test.

Figure 1: Cannibalization effects between firm's new and existing products in same ATC4 class.

(a) Large firms
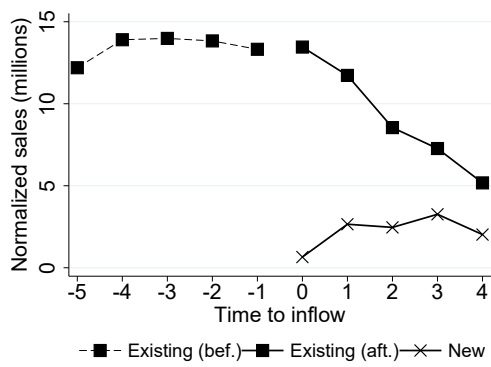
(b) Small firms
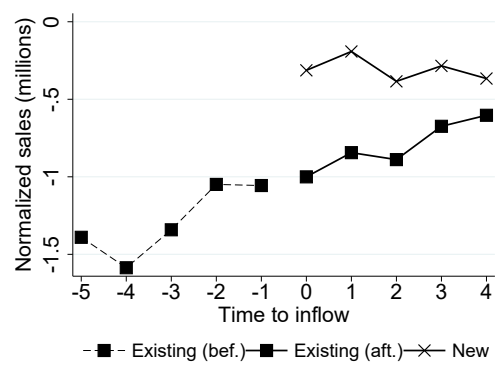
Supplemental Material: Uncovering the role of product innovation in the relation between firm size and growth

The Supplemental Material (SM) reports the following additional analyses and results: impact of drug patent expiry (SM1), attrition regressions (SM2), first-stage regressions (SM3), additional estimates (SM4), diagnostic tests (SM5), and finally the derivation of Equation 6 (SM6).

SM1. Influence of drug patent expiry on drug and firm sales

This Section examines the influence of drug patent expiry on firm sales and its possible role in the differential cannibalization effects observed between small and large firms. When the patent protection expires, generic manufacturers enter the market with drugs that are equivalent to the originator's drug, but with a significantly lower price. This can cause a sharp decline in sales of the innovator drug soon after the patent expiry, which is known as "patent cliff" (Harrison, 2011). Such patent cliff may have perceptible effects on firm sales as well, especially for major blockbuster drugs (Song and Han, 2016). Innovator firms often try to mitigate the patent cliff by launching variants of the lead drug near patent expiry, which may result in cannibalization of the lead drug.

While the decline in sales and market share after patent expiry has been well documented for several drugs (Ching, 2010), the dynamics of firm sales has received much less attention. We analyzed the influence of patent expiry on firm sales by collecting expiry dates of patents for US drugs from the FDA "Orange Book" (U.S. Food and Drug Administration, 2019). The US appear a valid case study because generic competition is particularly fierce in this country, and hence any possible impact on firm sales should be clearly detectable. We were able to match 258 US patents with expiry date within the period 1996-2008.[26] Figure SM1 reports the sales dynamics for the top selling products among those with a minimum number of observations around expiry. A patent cliff around expiry year can be clearly observed except in very few cases. Note that the cliff may appear with some delay because generic products enter the market typically a few years after expiry, due to the time required to adopt the manufacturing technology and to obtain approval for marketing (Ching, 2010). Moreover, the period of time covered by a patent normally lasts 20 years, although such period can be extended or shortened in some cases. Since these products are top seller drugs, the possible impact of patent cliff on firm sales should be mostly evident. Figure SM2 reports the sales dynamics of owner firms of these high selling products. In this case, it appears that patent expiry leads only a minority of firms to a sharp discontinuity, and the remaining set of firms to a mild slowdown at most.

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[26]For drugs with multiple patents over time, the earliest expiry date was considered.

Figure SM1: Patent cliff of high seller US products with patent expiry date in 1996-2008
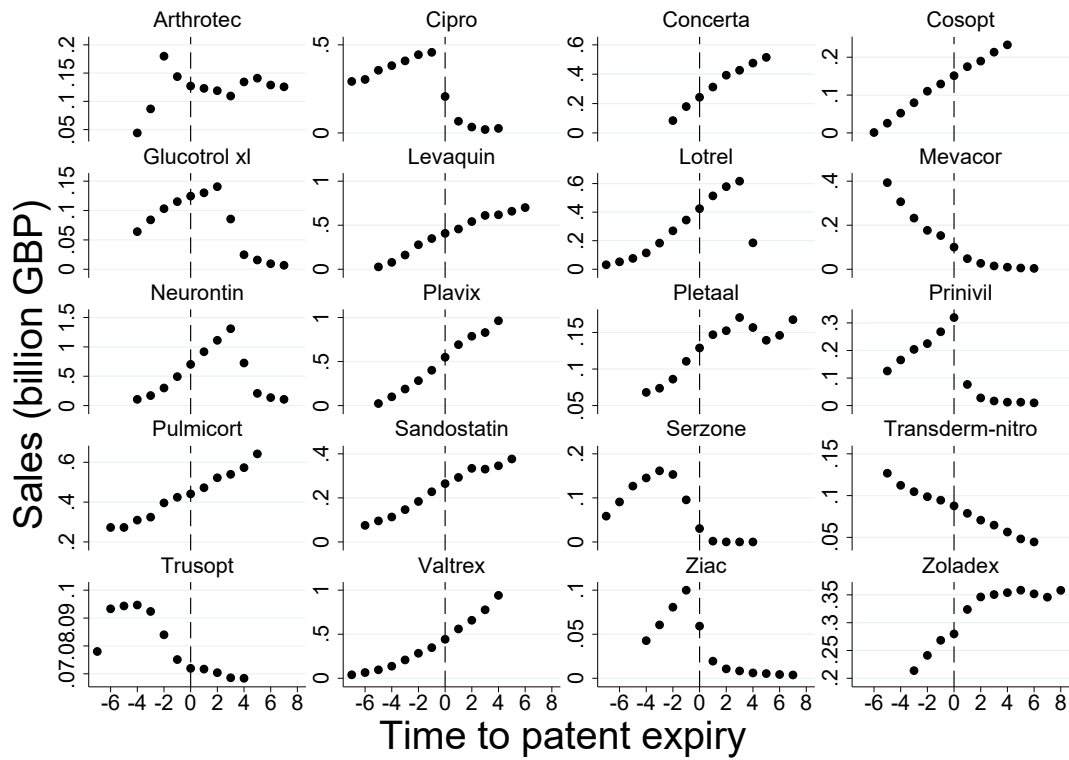
Figure SM2: Sales of firms owning high seller US products with patent expiry date in 1996-2008
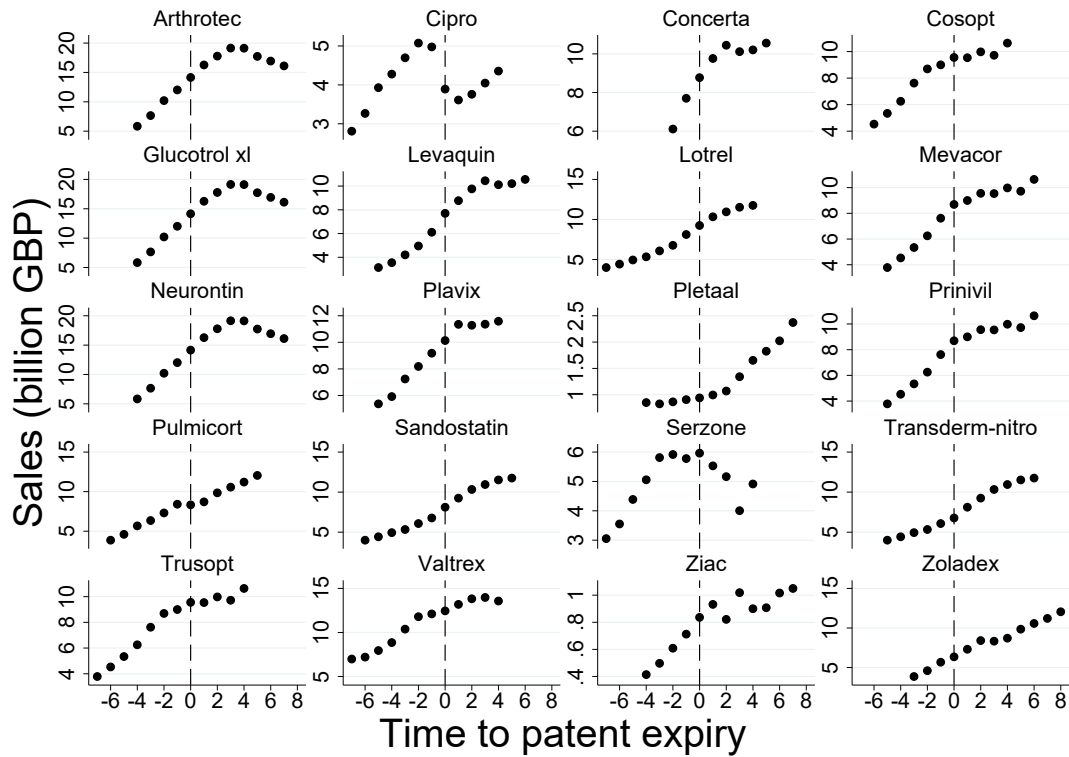
Figure SM3: Average growth of US products with patent expiry date in 1996-2008 and average growth of owning firms
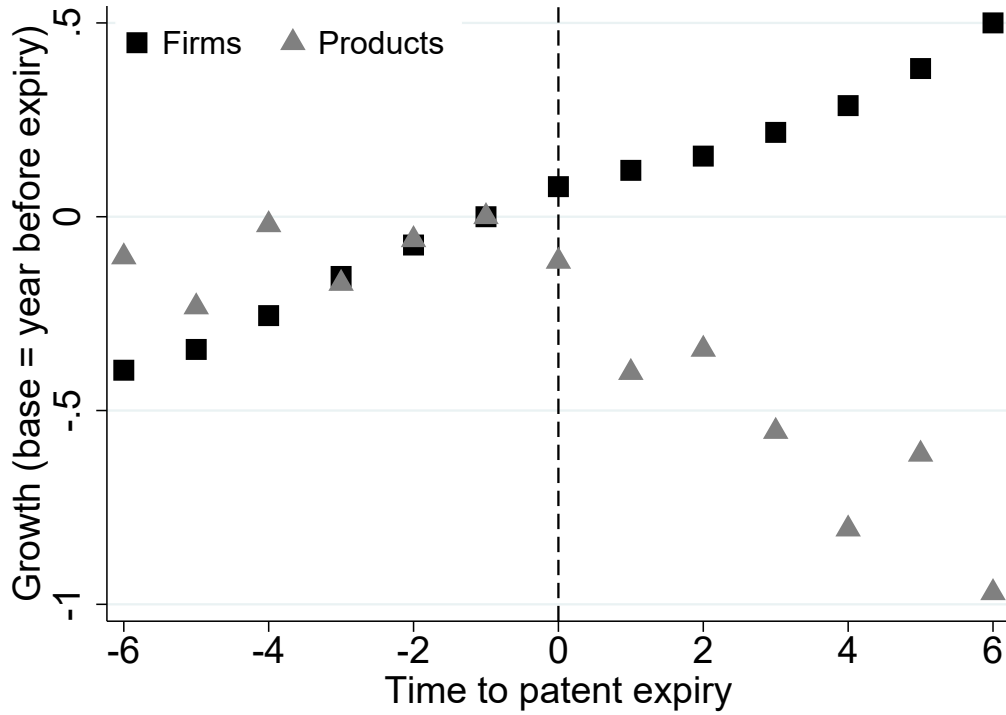
Figure SM4: Average growth of US products with patent expiry date in 1996-2008 and average growth of owning firms
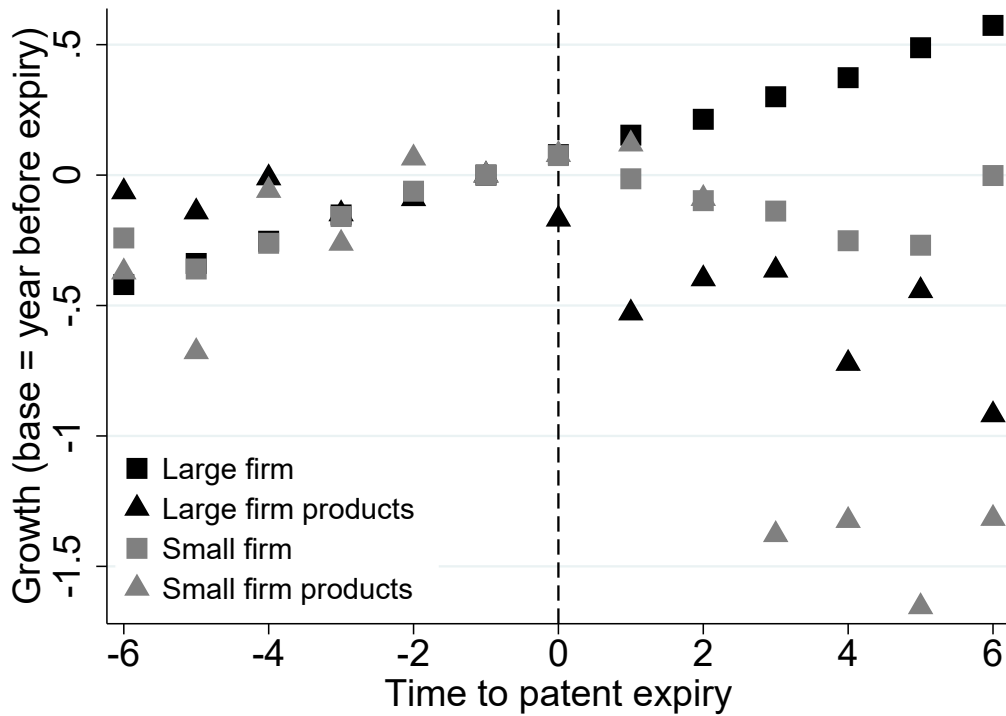
If we look at the total sample of patent expiries, we note that in the year before patent expiry, owner firms have 427 drugs and those near expiry account for only 5.8% of their sales on average. In order to assess the overall impact of patent expiries on firm sales, we calculated the average growth rate of firm sales by time to expiry. The growth dynamics is reported in Figure SM3. The growth rate was calculated using the year before expiry as a reference to remove year effects. Figure SM3 shows that, firms owning a drug going through patent expiry experience only a minor deviation from their trend. This is in clear contrast with the sharp discontinuity that can be clearly observed for products. Therefore, it appears that firms owning such products can compensate rather well the effects of competition from generic manufacturers. Since patent expiries occur for a negligible portion of all products marketed in the period considered, the observed impact on firm sales is unlikely to have any meaningful relevance for the US market as a whole. Furthermore, since the generics share is particularly high in the US, this impact should not be any larger in other countries. Therefore, the present evidence suggests overall that patent cliffs may have minimal influence on estimation of the size-growth relation.

Similarly, it is quite unlikely that patent expiries may have a quantitatively relevant influence on the differential cannibalization effect between small and large firms. This issue was investigated by separating the sample of firms going through patent expiry between small and large firms, where the former have been defined by all firms with an average sales value below the 25th percentile. Figure SM4 compares the growth dynamics of patented drugs and owning firms for the two samples. This Figures points out a divergence after patent expiry in the growth trend of firm sales, with large firms being minimally affected, and smaller firms exhibiting a decline. It is hence possible that larger firms manage to mitigate the patent cliff by extensions of the brand-line, which may in turn cannibalize the lead drug. However, since larger firms appear to attenuate to a greater extent also the patent cliff of the lead drug, there is no evidence that they experience larger cannibalization effects.

SM2. Attrition regressions

Table SM1: Selection yearly regressions for models in Table 2

	2002	2003	2004	2005	2006	2007	2008
$ln(S_{-2})$	0.2646**	0.2597**	0.2516**	0.2380**	0.1995**	0.1835**	0.2099**
	(0.0385)	(0.0353)	(0.0262)	(0.0358)	(0.0237)	(0.0274)	(0.0262)
$Age = 11-20$	0.0799	−0.7023**	0.2568	0.2754	−0.2107	0.5313*	−0.1671
	(0.2264)	(0.2196)	(0.1893)	(0.2044)	(0.1594)	(0.2226)	(0.2311)
$Age = 21-50$	0.1989	−0.1346	0.1774	0.1851	0.0467	0.3423	−0.2003
	(0.2129)	(0.2533)	(0.1781)	(0.2133)	(0.1739)	(0.1872)	(0.2238)
$Age > 50$	0.4532	−0.4035	−0.1469	0.3274	0.3170	0.5726*	−0.4043
	(0.4009)	(0.2952)	(0.2229)	(0.3037)	(0.2955)	(0.2833)	(0.2642)
k^{in}_{-1} (%)	0.0098	0.0304*	0.0063	0.0201	0.0094		
	(0.0067)	(0.0121)	(0.0045)	(0.0171)	(0.0062)		
k^{out}_{-1} (%)	−0.0105*	−0.0214**	−0.0042	−0.0129**	−0.0033	−0.0158**	−0.0109*
	(0.0050)	(0.0056)	(0.0043)	(0.0047)	(0.0046)	(0.0036)	(0.0046)
k^{out}_{-2} (%)	−0.0082	−0.0095*	−0.0074	−0.0033	0.0069	0.0006	−0.0019
	(0.0060)	(0.0046)	(0.0050)	(0.0044)	(0.0063)	(0.0049)	(0.0053)
$ln(atcmain)_{-1}$	−0.0176	−1.1583*	−0.9052**	−0.7643*	−1.6035**	−0.6667	−1.5526*
	(0.2869)	(0.4601)	(0.3002)	(0.3313)	(0.5444)	(0.3653)	(0.6202)
Obs.	1938	1981	2012	2038	2089	2113	2150

Notes: * significant 5%, ** significant 1%. Robust standard errors are reported in parenthesis. Some covariates may be dropped in some years in case they perfectly predict selection.

Table SM2: Selection yearly regressions for models in Table 4 (Stable portfolio)

	2002	2003	2004	2005	2006	2007	2008
$ln(S_{-2})$	0.3222**	0.3208**	0.2409**	0.1924**	0.1716**	0.1937**	0.2503**
	(0.0597)	(0.0428)	(0.0384)	(0.0403)	(0.0273)	(0.0372)	(0.0378)
$Age \leq 10$	−0.0898						0.0790
	(0.2528)						(0.2503)
$Age = 11 - 20$		−0.1440	0.2570	0.1014	−0.1643	0.4560	
		(0.2697)	(0.2604)	(0.2358)	(0.1981)	(0.3474)	
$Age = 21 - 50$		−0.3226	0.0407	0.1150	0.0118	0.7665	
		(0.2876)	(0.2691)	(0.2925)	(0.2391)	(0.4387)	
$Age > 50$		0.0963	−0.5466	−0.0658	0.1989	0.1014	
		(0.3830)	(0.3352)	(0.5203)	(0.5131)	(0.4780)	
$ln(atcmain)_{-1}$	0.8237	−3.4315	−1.8068	0.2480	−0.3017	0.5731	−0.4487
	(0.8073)	(2.0423)	(1.2059)	(0.5741)	(0.5570)	(0.4722)	(0.7480)
Obs.	375	394	422	438	475	471	515

Notes: * significant 5%, ** significant 1%. Robust standard errors are reported in parenthesis. Some covariates may be dropped in some years in case they perfectly predict selection.

Table SM3: Selection yearly regressions for models in Table 4 (Variable portfolio) and for models in Table SM20

	2002	2003	2004	2005	2006	2007	2008
$ln(S_{-2})$	0.1918**	0.2090**	0.2315**	0.2564**	0.2390**	0.1709**	0.1838**
	(0.0532)	(0.0451)	(0.0331)	(0.0546)	(0.0379)	(0.0362)	(0.0314)
$Age = 11-20$	0.1853	−0.8722**	0.2002	0.6283	−0.2347	0.5342	−0.0934
	(0.3066)	(0.3058)	(0.2672)	(0.3722)	(0.2397)	(0.2865)	(0.3053)
$Age = 21-50$	0.6441*	−0.0137	0.2034	0.2378	0.0048	0.2378	−0.0665
	(0.3148)	(0.3572)	(0.2342)	(0.2991)	(0.2417)	(0.2177)	(0.2985)
$Age > 50$	0.3816	−0.5620	−0.0244	0.5396	0.2441	0.6981*	−0.3664
	(0.4051)	(0.3782)	(0.2969)	(0.3370)	(0.3733)	(0.3462)	(0.3039)
k^{in}_{-1} (%)	0.0085	0.0319**	0.0051				
	(0.0063)	(0.0118)	(0.0042)				
k^{out}_{-1} (%)	−0.0130*	−0.0240**	−0.0068	−0.0171**	−0.0022	−0.0162**	−0.0099*
	(0.0055)	(0.0060)	(0.0044)	(0.0054)	(0.0054)	(0.0041)	(0.0048)
k^{out}_{-2} (%)	−0.0130*	−0.0127**	−0.0105*	−0.0075	0.0033	−0.0007	−0.0010
	(0.0065)	(0.0049)	(0.0053)	(0.0050)	(0.0064)	(0.0050)	(0.0055)
$ln(atcmain)_{-1}$	−0.0060	−1.1654*	−0.6280*	−0.7141	−1.9315*	−1.0934	−1.7012**
	(0.2967)	(0.4897)	(0.2775)	(0.3684)	(0.9522)	(0.5903)	(0.6594)
Obs.	1602	1627	1648	1655	1680	1690	1704

Notes: * significant 5%, ** significant 1%. Robust standard errors are reported in parenthesis. Some covariates may be dropped in some years in case they perfectly predict selection.

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Table SM4: Selection yearly regressions for models in Table 6, Table SM16 and Table SM17

	2002	2003	2004	2005	2006	2007	2008
$ln(K_{-2})$	0.0313	−0.1841	−0.0534	−0.0983	0.3916**	−0.0615	0.0098
	(0.1064)	(0.1443)	(0.1147)	(0.1460)	(0.1490)	(0.1044)	(0.1697)
$ln(S_{-2})$	0.1722**	0.3201**	0.2580**	0.2543**	0.2302**	0.1896**	0.1841**
	(0.0452)	(0.0386)	(0.0346)	(0.0508)	(0.0365)	(0.0375)	(0.0320)
$Age = 11 - 20$	0.0246	−0.8519**	0.1237	0.5151	−0.1945	0.4883	−0.1893
	(0.2545)	(0.2309)	(0.2509)	(0.3637)	(0.2424)	(0.2684)	(0.2957)
$Age = 21 - 50$	0.4979	−0.2015	0.0921	0.0561	0.0957	0.1884	−0.1396
	(0.2644)	(0.2612)	(0.2221)	(0.2601)	(0.2384)	(0.2057)	(0.2867)
$Age > 50$	0.4542	−0.3873	−0.1275	0.2514	0.2816	0.5638	−0.4224
	(0.4093)	(0.3480)	(0.2712)	(0.3350)	(0.3677)	(0.3254)	(0.2983)
$ln(atcmain)_{-1}$	−0.3710	−1.3283**	−0.7270*	−0.9891*	−1.2645	−1.2764*	−1.7530*
	(0.3752)	(0.4053)	(0.3171)	(0.4388)	(0.8989)	(0.6373)	(0.8403)
Obs.	1647	1683	1690	1700	1721	1734	1749

Notes: * significant 5%, ** significant 1%. Robust standard errors are reported in parenthesis. Some covariates may be dropped in some years in case they perfectly predict selection.

Table SM5: Selection yearly regressions for models in Table SM18 and Table SM19

	2002	2003	2004	2005	2006	2007	2008
$ln(S_{-2})$	0.1538**	0.1883**	0.2233**	0.2391**	0.1984**	0.1458**	0.1587**
	(0.0519)	(0.0460)	(0.0361)	(0.0559)	(0.0386)	(0.0372)	(0.0312)
$ln(K_{-2})$	0.3488**	0.1765	0.0777	0.1747	0.6102**	0.2879*	0.2643
	(0.1348)	(0.2067)	(0.1550)	(0.1979)	(0.1813)	(0.1248)	(0.1682)
$Age = 11-20$	0.1895	−0.8903**	0.1923	0.6307	−0.2871	0.5279	−0.0711
	(0.3086)	(0.3065)	(0.2690)	(0.3690)	(0.2438)	(0.2873)	(0.3064)
$Age = 21-50$	0.6018	−0.0113	0.2027	0.2389	0.0312	0.2749	−0.0211
	(0.3103)	(0.3535)	(0.2341)	(0.2980)	(0.2452)	(0.2170)	(0.2921)
$Age > 50$	0.3663	−0.5927	−0.0491	0.5100	0.2591	0.6852	−0.3486
	(0.4072)	(0.3842)	(0.2841)	(0.3360)	(0.3838)	(0.3506)	(0.2990)
k^{in}_{-1} (%)	0.0101	0.0308**	0.0053				
	(0.0054)	(0.0119)	(0.0041)				
k^{out}_{-1} (%)	−0.0170**	−0.0267**	−0.0077	−0.0198**	−0.0115*	−0.0198**	−0.0135**
	(0.0055)	(0.0060)	(0.0048)	(0.0060)	(0.0058)	(0.0041)	(0.0043)
k^{out}_{-2} (%)	−0.0128*	−0.0123*	−0.0105*	−0.0068	0.0031	−0.0013	−0.0014
	(0.0063)	(0.0048)	(0.0052)	(0.0048)	(0.0059)	(0.0048)	(0.0053)
$ln(atcmain)_{-1}$	0.5447	−0.8204	−0.4990	−0.4171	−0.7528	−0.5449	−1.1010
	(0.3358)	(0.5876)	(0.3577)	(0.4136)	(0.7819)	(0.5311)	(0.6864)
Obs.	1602	1627	1648	1655	1680	1690	1704

Notes: * significant 5%, ** significant 1%. Robust standard errors are reported in parenthesis. Some covariates may be dropped in some years in case they perfectly predict selection.

SM3. First-stage regression results

Table SM6: Size-Growth regressions. First-stage results (see Table 2). The endogenous variable is $ln(S_{-1})$.

	FD-IV	FD-IV-ATT
$ln(S_{-2})$	0.2564**	0.2429**
	(0.0176)	(0.0179)
$ln(S_{-3})$	0.0912**	0.0802**
	(0.0166)	(0.0167)
$ln(S_{-4})$	0.0435**	0.0385*
	(0.0158)	(0.0157)
$Age = 11 - 20$	−0.0099	−0.0049
	(0.0210)	(0.0212)
$Age = 21 - 50$	−0.0311	−0.0266
	(0.0426)	(0.0424)
$Age > 50$	−0.0249	−0.0287
	(0.0466)	(0.0464)
k^{in} (%)	−0.0005**	−0.0005**
	(0.0002)	(0.0002)
k^{in}_{-1} (%)	−0.0000	−0.0000
	(0.0002)	(0.0002)
k^{out} (%)	−0.0007	−0.0010*
	(0.0004)	(0.0004)
$newmol$	−0.0028	−0.0029
	(0.0073)	(0.0072)
$newmol_{-1}$	0.0266**	0.0260**
	(0.0087)	(0.0086)
$newmol_{-2}$	0.0450**	0.0444**
	(0.0072)	(0.0072)
$ln(atcmain)_{-1}$	0.0687	0.0786*
	(0.0373)	(0.0370)
$atcd_{-1}$	−0.0254*	−0.0254*
	(0.0103)	(0.0103)
Year FE	Yes	Yes
Year FE $\times$ IMR	No	Yes
Obs.	12860	12860
Firms	2173	2173

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM7: Size-Growth regressions. First-stage results (see Table 4). The endogenous variable is $ln(S_{-1})$.

	Stable portfolio		Variable portfolio	
	FD-IV	FD-IV-ATT	FD-IV	FD-IV-ATT
$ln(S_{-2})$	0.1700**	0.1752**	0.2797**	0.2631**
	(0.0434)	(0.0439)	(0.0189)	(0.0193)
$ln(S_{-3})$	0.1195**	0.1217**	0.0775**	0.0639**
	(0.0371)	(0.0379)	(0.0186)	(0.0184)
$ln(S_{-4})$	0.0257	0.0299	0.0473**	0.0410*
	(0.0350)	(0.0352)	(0.0177)	(0.0174)
$Age = 11 - 20$	−0.0455	−0.0489	0.0091	0.0142
	(0.0439)	(0.0446)	(0.0239)	(0.0239)
$Age = 21 - 50$	−0.0685	−0.0751	−0.0080	−0.0019
	(0.0893)	(0.0900)	(0.0483)	(0.0478)
$Age > 50$	−0.1884	−0.1921	0.0062	0.0049
	(0.1147)	(0.1154)	(0.0520)	(0.0516)
k^{in} (%)			−0.0004**	−0.0004**
			(0.0002)	(0.0002)
k^{in}_{-1} (%)			0.0000	−0.0000
			(0.0002)	(0.0002)
k^{out} (%)			−0.0006	−0.0011**
			(0.0004)	(0.0004)
$newmol$			−0.0032	−0.0035
			(0.0072)	(0.0071)
$newmol_{-1}$			0.0272**	0.0256**
			(0.0086)	(0.0085)
$newmol_{-2}$			0.0452**	0.0433**
			(0.0072)	(0.0071)
$ln(atcmain)_{-1}$	0.7049*	0.7056*	0.0587	0.0731*
	(0.3238)	(0.3216)	(0.0376)	(0.0372)
$atcd_{-1}$			−0.0248*	−0.0249*
			(0.0104)	(0.0104)
Year FE	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes
Obs.	2026	2026	10834	10834
Firms	440	440	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM8: Size-Growth regressions. First-stage results (see Table SM15).

	Stable portfolio		Variable portfolio	
	FD-IV	FD-IV-ATT	FD-IV	FD-IV-ATT
$ln(S_{-2})$	0.1723**	0.1774**	0.2839**	0.2655**
	(0.0426)	(0.0432)	(0.0185)	(0.0190)
$ln(S_{-3})$	0.1243**	0.1270**	0.0897**	0.0735**
	(0.0358)	(0.0366)	(0.0176)	(0.0174)
$Age = 11 - 20$	-0.0460	-0.0493	0.0122	0.0176
	(0.0438)	(0.0445)	(0.0240)	(0.0240)
$Age = 21 - 50$	-0.0702	-0.0767	-0.0080	-0.0011
	(0.0893)	(0.0901)	(0.0481)	(0.0476)
$Age > 50$	-0.1885	-0.1922	0.0061	0.0055
	(0.1147)	(0.1154)	(0.0519)	(0.0515)
k^{in} (%)			-0.0004**	-0.0004**
			(0.0002)	(0.0002)
k^{in}_{-1} (%)			0.0000	-0.0000
			(0.0002)	(0.0002)
k^{out} (%)			-0.0006	-0.0011**
			(0.0004)	(0.0004)
$newmol$			-0.0034	-0.0036
			(0.0072)	(0.0071)
$newmol_{-1}$			0.0273**	0.0258**
			(0.0086)	(0.0085)
$newmol_{-2}$			0.0458**	0.0439**
			(0.0072)	(0.0071)
$ln(atcmain)_{-1}$	0.7017*	0.7017*	0.0549	0.0705
	(0.3251)	(0.3232)	(0.0375)	(0.0371)
$atcd_{-1}$			-0.0258*	-0.0258*
			(0.0104)	(0.0104)
Year FE	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes
Obs.	2026	2026	10834	10834
Firms	440	440	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM9: Size-Growth regressions. First-stage results (see Table 6). The endogenous variable is $ln(K_{-1})$.

	FD-IV	FD-IV-ATT
$ln(K_{-3})$	0.0388**	0.0389**
	(0.0148)	(0.0151)
$ln(K_{-4})$	0.0453**	0.0423**
	(0.0114)	(0.0113)
$ln(S_{-2})$	0.0754**	0.0705**
	(0.0080)	(0.0082)
$ln(S_{-1})$	0.1191**	0.1181**
	(0.0088)	(0.0088)
$Age = 11 - 20$	0.0323*	0.0341*
	(0.0133)	(0.0134)
$Age = 21 - 50$	0.0142	0.0173
	(0.0209)	(0.0209)
$Age > 50$	0.0118	0.0132
	(0.0241)	(0.0241)
$newmol_{-1}$	0.1331**	0.1329**
	(0.0058)	(0.0058)
$newmol_{-2}$	0.0921**	0.0922**
	(0.0056)	(0.0056)
$newmol_{-3}$	0.0407**	0.0405**
	(0.0042)	(0.0042)
$ln(atcmain)_{-1}$	−0.2170**	−0.2147**
	(0.0175)	(0.0174)
$atcd_{-1}$	0.0028	0.0024
	(0.0040)	(0.0040)
Year FE	Yes	Yes
Year FE × IMR	No	Yes
Obs.	10834	10834
Firms	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM10: Relation between firm size (S) and products inflow rate. Sample of firms with variable portfolio. First-stage results (see Table SM16). The endogenous variable is $ln(K_{-1})$.

	FD-IV	FD-IV-ATT
$ln(K_{-3})$	0.0388**	0.0389**
	(0.0148)	(0.0151)
$ln(K_{-4})$	0.0453**	0.0423**
	(0.0114)	(0.0113)
$ln(S_{-2})$	0.0754**	0.0705**
	(0.0080)	(0.0082)
$ln(S_{-1})$	0.1191**	0.1181**
	(0.0088)	(0.0088)
$Age = 11 - 20$	0.0323*	0.0341*
	(0.0133)	(0.0134)
$Age = 21 - 50$	0.0142	0.0173
	(0.0209)	(0.0209)
$Age > 50$	0.0118	0.0132
	(0.0241)	(0.0241)
$newmol_{-1}$	0.1331**	0.1329**
	(0.0058)	(0.0058)
$newmol_{-2}$	0.0921**	0.0922**
	(0.0056)	(0.0056)
$newmol_{-3}$	0.0407**	0.0405**
	(0.0042)	(0.0042)
$ln(atcmain)_{-1}$	−0.2170**	−0.2147**
	(0.0175)	(0.0174)
$atcd_{-1}$	0.0028	0.0024
	(0.0040)	(0.0040)
Year FE	Yes	Yes
Year FE × IMR	No	Yes
Obs.	10834	10834
Firms	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM11: Size-Growth regressions. First-stage results (see Table SM17). The endogenous variable is $ln(K_{-1})$.

	FD-IV	FD-IV-ATT
$ln(K_{-3})$	0.0637**	0.0595**
	(0.0152)	(0.0154)
$ln(S_{-1})$	0.1419**	0.1377**
	(0.0088)	(0.0089)
$Age = 11 - 20$	0.0318*	0.0361**
	(0.0135)	(0.0136)
$Age = 21 - 50$	0.0065	0.0127
	(0.0214)	(0.0213)
$Age > 50$	0.0029	0.0060
	(0.0246)	(0.0244)
$newmol_{-1}$	0.1292**	0.1294**
	(0.0057)	(0.0057)
$newmol_{-2}$	0.0889**	0.0892**
	(0.0056)	(0.0056)
$newmol_{-3}$	0.0349**	0.0353**
	(0.0040)	(0.0040)
$ln(atcmain)_{-1}$	−0.2305**	−0.2255**
	(0.0179)	(0.0177)
$atcd_{-1}$	0.0019	0.0014
	(0.0040)	(0.0040)
Year FE	Yes	Yes
Year FE × IMR	No	Yes
Obs.	10834	10834
Firms	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM12: Relation between firm size (S) and average sales ratio - new vs existing products. Sample of firms with variable portfolio. First-stage results (see Table SM18). The endogenous variable is $ln(1 + R^{in}_{-1})$.

	FD-IV	FD-IV-ATT
$ln(1 + R^{in}_{-2})$	-0.6347^{**}	-0.6348^{**}
	(0.0157)	(0.0157)
$ln(1 + R^{in}_{-3})$	-0.2938^{**}	-0.2937^{**}
	(0.0116)	(0.0116)
$ln(S_{-1})$	0.1111^{**}	0.1118^{**}
	(0.0118)	(0.0119)
$ln(K_{-1})$	-0.0081	-0.0045
	(0.0211)	(0.0214)
$Age = 11 - 20$	-0.0098	-0.0104
	(0.0169)	(0.0170)
$Age = 21 - 50$	-0.0342	-0.0349
	(0.0300)	(0.0301)
$Age > 50$	-0.0353	-0.0353
	(0.0370)	(0.0370)
k^{in} (%)	-0.0002	-0.0002
	(0.0001)	(0.0001)
k^{in}_{-1} (%)	0.0003	0.0003
	(0.0002)	(0.0002)
k^{out} (%)	0.0001	0.0001
	(0.0002)	(0.0002)
$newmol$	-0.0073	-0.0076
	(0.0078)	(0.0078)
$newmol_{-1}$	0.1493^{**}	0.1486^{**}
	(0.0104)	(0.0104)
$newmol_{-2}$	0.0725^{**}	0.0721^{**}
	(0.0084)	(0.0084)
$ln(atcmain)_{-1}$	-0.1279^{**}	-0.1285^{**}
	(0.0364)	(0.0364)
$atcd_{-1}$	0.0562^{**}	0.0562^{**}
	(0.0101)	(0.0101)
Year FE	Yes	Yes
Year FE $\times$ IMR	No	Yes
Obs.	10834	10834
Firms	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM13: Relation between firm size (S) and average sales ratio - old vs existing products. Sample of firms with variable portfolio. First-stage results (see Table SM19). The endogenous variable is $ln(1 + R_{-1}^{out})$.

	FD-IV	FD-IV-ATT
$ln(1 + R_{-2}^{out})$	-0.6821^{**}	-0.6800^{**}
	(0.0218)	(0.0218)
$ln(1 + R_{-3}^{out})$	-0.3496^{**}	-0.3482^{**}
	(0.0232)	(0.0232)
$ln(S_{-1})$	-0.0446^{**}	-0.0451^{**}
	(0.0071)	(0.0072)
$ln(K_{-1})$	-0.0462^{**}	-0.0520^{**}
	(0.0107)	(0.0106)
$Age = 11 - 20$	0.0115	0.0124
	(0.0081)	(0.0080)
$Age = 21 - 50$	0.0103	0.0118
	(0.0136)	(0.0136)
$Age > 50$	0.0055	0.0072
	(0.0180)	(0.0180)
k^{in} (%)	-0.0002^{**}	-0.0002^{**}
	(0.0001)	(0.0001)
k_{-1}^{in} (%)	0.0000	0.0000
	(0.0000)	(0.0000)
k^{out} (%)	-0.0010^{**}	-0.0010^{**}
	(0.0001)	(0.0001)
$newmol$	0.0005	0.0006
	(0.0028)	(0.0028)
$newmol_{-1}$	0.0042	0.0048
	(0.0032)	(0.0032)
$newmol_{-2}$	0.0044	0.0048
	(0.0027)	(0.0026)
$ln(atcmain)_{-1}$	0.0757^{**}	0.0756^{**}
	(0.0132)	(0.0131)
$atcd_{-1}$	0.0185^{**}	0.0183^{**}
	(0.0041)	(0.0041)
Year FE	Yes	Yes
Year FE × IMR	No	Yes
Obs.	10834	10834
Firms	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

Table SM14: Relation between firm size (S) and sales growth rate of stable products. Sample of firms with variable portfolio. First-stage results (see Table SM20). The endogenous variable is $ln(S_{-1})$.

	FD-IV	FD-IV-ATT
$ln(S_{-2})$	0.2839**	0.2655**
	(0.0185)	(0.0190)
$ln(S_{-3})$	0.0897**	0.0735**
	(0.0176)	(0.0174)
$Age = 11-20$	0.0122	0.0176
	(0.0240)	(0.0240)
$Age = 21-50$	-0.0080	-0.0011
	(0.0481)	(0.0476)
$Age > 50$	0.0061	0.0055
	(0.0519)	(0.0515)
k^{in} (%)	-0.0004**	-0.0004**
	(0.0002)	(0.0002)
k^{in}_{-1} (%)	0.0000	-0.0000
	(0.0002)	(0.0002)
k^{out} (%)	-0.0006	-0.0011**
	(0.0004)	(0.0004)
$newmol$	-0.0034	-0.0036
	(0.0072)	(0.0071)
$newmol_{-1}$	0.0273**	0.0258**
	(0.0086)	(0.0085)
$newmol_{-2}$	0.0458**	0.0439**
	(0.0072)	(0.0071)
$ln(atcmain)_{-1}$	0.0549	0.0705
	(0.0375)	(0.0371)
$atcd_{-1}$	-0.0258*	-0.0258*
	(0.0104)	(0.0104)
Year FE	Yes	Yes
Year FE $\times$ IMR	No	Yes
Obs.	10834	10834
Firms	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust.

SM4. Additional results

Table SM15: Size-Growth regressions. Firms with and without product flows: alternative instruments set (see Table 4)

	Stable portfolio				Variable portfolio			
	FD-2S	FD-2S-ATT	FD-GMM	FD-GMM-ATT	FD-2S	FD-2S-ATT	FD-GMM	FD-GMM-ATT
$ln(S_{-1})$	1.0811**	0.9224**	1.0695**	0.9152**	0.7388**	0.6411**	0.7518**	0.6498**
	(0.1701)	(0.1667)	(0.1688)	(0.1657)	(0.0529)	(0.0602)	(0.0510)	(0.0590)
$Age = 11-20$	−0.1032	−0.1103	−0.1104	−0.1164	−0.0739*	−0.0619*	−0.0739*	−0.0616*
	(0.0711)	(0.0687)	(0.0699)	(0.0668)	(0.0319)	(0.0314)	(0.0319)	(0.0314)
$Age = 21-50$	−0.1591	−0.1759	−0.1662	−0.1813	−0.0776	−0.0648	−0.0756	−0.0632
	(0.1220)	(0.1118)	(0.1213)	(0.1118)	(0.0517)	(0.0501)	(0.0516)	(0.0506)
$Age > 50$	0.0553	0.0177	0.0464	0.0107	−0.0911	−0.0798	−0.0896	−0.0783
	(0.1735)	(0.1673)	(0.1728)	(0.1631)	(0.0581)	(0.0568)	(0.0581)	(0.0572)
k^{in} (%)					0.0010**	0.0009**	0.0010**	0.0009**
					(0.0003)	(0.0003)	(0.0003)	(0.0003)
k^{in}_{-1} (%)					0.0008*	0.0007*	0.0008*	0.0007*
					(0.0003)	(0.0003)	(0.0003)	(0.0003)
k^{out} (%)					−0.0026**	−0.0030**	−0.0025**	−0.0030**
					(0.0005)	(0.0005)	(0.0005)	(0.0005)
$newmol$					0.0291**	0.0303**	0.0294**	0.0305**
					(0.0098)	(0.0096)	(0.0098)	(0.0096)
$newmol_{-1}$					0.0596**	0.0632**	0.0591**	0.0629**
					(0.0103)	(0.0102)	(0.0103)	(0.0103)
$newmol_{-2}$					0.0352**	0.0396**	0.0351**	0.0395**
					(0.0083)	(0.0082)	(0.0083)	(0.0082)
$ln(atcmain)_{-1}$	−0.5673	−0.4601	−0.5469	−0.4445	−0.1374**	−0.1205**	−0.1399**	−0.1220**
	(0.3404)	(0.2993)	(0.3385)	(0.3062)	(0.0341)	(0.0322)	(0.0340)	(0.0323)
$atcd_{-1}$					0.0331**	0.0287*	0.0326**	0.0284*
					(0.0124)	(0.0116)	(0.0124)	(0.0116)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	2026	2026	2026	2026	10834	10834	10834	10834
Firms	440	440	440	440	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(S_{-1})$ is instrumented with the following IVs: $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$. The reported coefficient on $ln(S_{-1})$ is $\tilde{\beta}$; $\tilde{\beta} \neq 1$ corresponds to $\beta \neq 0$.

Table SM16: Relation between firm size (S) and products inflow rate. Sample of firms with variable portfolio. Dependent variable is $ln(1 + k^{in})$

	OLS	FE	FD-2S	FD-GMM	FD-2S-ATT	FD-GMM-ATT
$ln(S_{-1})$	0.0039**	0.0207**	−0.0159	−0.0119	−0.0151	−0.0109
	(0.0006)	(0.0039)	(0.0107)	(0.0103)	(0.0112)	(0.0110)
$ln(K_{-1})$	−0.0162**	−0.1244**	−0.0220	−0.0405	−0.0261	−0.0469
	(0.0020)	(0.0123)	(0.0563)	(0.0548)	(0.0626)	(0.0628)
$Age = 11 - 20$	−0.0221**	−0.0037	−0.0128	−0.0125	−0.0122	−0.0119
	(0.0059)	(0.0089)	(0.0123)	(0.0123)	(0.0126)	(0.0129)
$Age = 21 - 50$	−0.0318**	−0.0066	−0.0028	−0.0026	−0.0031	−0.0030
	(0.0054)	(0.0134)	(0.0165)	(0.0165)	(0.0167)	(0.0173)
$Age > 50$	−0.0422**	−0.0120	−0.0051	−0.0036	−0.0053	−0.0040
	(0.0054)	(0.0159)	(0.0194)	(0.0194)	(0.0195)	(0.0196)
$newmol_{-1}$	0.0287**	−0.0062*	−0.0994**	−0.0961**	−0.0989**	−0.0953**
	(0.0028)	(0.0031)	(0.0091)	(0.0088)	(0.0098)	(0.0096)
$newmol_{-2}$	0.0157**	−0.0103**	−0.0615**	−0.0602**	−0.0613**	−0.0598**
	(0.0029)	(0.0031)	(0.0063)	(0.0062)	(0.0068)	(0.0067)
$newmol_{-3}$	0.0084**	−0.0079**	−0.0249**	−0.0242**	−0.0247**	−0.0239**
	(0.0027)	(0.0029)	(0.0037)	(0.0036)	(0.0039)	(0.0038)
$ln(atcmain)_{-1}$	−0.0004	−0.0058	0.0606**	0.0556**	0.0593**	0.0538**
	(0.0022)	(0.0067)	(0.0172)	(0.0169)	(0.0182)	(0.0178)
$atcd_{-1}$	0.0032	−0.0044	−0.0060	−0.0058	−0.0060	−0.0058
	(0.0031)	(0.0033)	(0.0034)	(0.0034)	(0.0034)	(0.0033)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	No	No	No	Yes	Yes
Obs.	10834	10834	10834	10834	10834	10834
Firms	1733	1733	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(K_{-1})$ is instrumented with the following IVs: $\Delta ln(K_{-3})$, $\Delta ln(K_{-4})$ $\Delta ln(S_{-2})$.

Table SM17: Relation between firm size (S) and products outflow rate. Sample of firms with variable portfolio. Dependent variable is $ln(1 + k^{out})$

	OLS	FE	FD-2S	FD-GMM	FD-2S-ATT	FD-GMM-ATT
$ln(S_{-1})$	−0.0095**	−0.0375**	−0.0093	−0.0093	−0.0069	−0.0069
	(0.0005)	(0.0030)	(0.0161)	(0.0161)	(0.0230)	(0.0230)
$ln(K_{-1})$	0.0304**	0.1529**	0.0541	0.0541	0.0264	0.0264
	(0.0012)	(0.0067)	(0.1028)	(0.1028)	(0.1560)	(0.1560)
$Age = 11 - 20$	−0.0011	−0.0134*	−0.0035	−0.0035	−0.0008	−0.0008
	(0.0038)	(0.0062)	(0.0092)	(0.0092)	(0.0111)	(0.0111)
$Age = 21 - 50$	0.0042	−0.0158	−0.0111	−0.0111	−0.0086	−0.0086
	(0.0034)	(0.0105)	(0.0149)	(0.0149)	(0.0161)	(0.0161)
$Age > 50$	0.0082*	−0.0254*	−0.0126	−0.0126	−0.0114	−0.0114
	(0.0036)	(0.0124)	(0.0163)	(0.0163)	(0.0174)	(0.0174)
$newmol_{-1}$	−0.0103**	−0.0187**	−0.0051	−0.0051	−0.0014	−0.0014
	(0.0020)	(0.0022)	(0.0132)	(0.0132)	(0.0200)	(0.0200)
$newmol_{-2}$	−0.0021	−0.0108**	−0.0021	−0.0021	0.0005	0.0005
	(0.0021)	(0.0024)	(0.0092)	(0.0092)	(0.0136)	(0.0136)
$newmol_{-3}$	−0.0008	−0.0104**	−0.0035	−0.0035	−0.0024	−0.0024
	(0.0022)	(0.0021)	(0.0046)	(0.0046)	(0.0065)	(0.0065)
$ln(atcmain)_{-1}$	0.0355**	0.0633**	−0.0001	−0.0001	−0.0047	−0.0047
	(0.0022)	(0.0065)	(0.0257)	(0.0257)	(0.0375)	(0.0375)
$atcd_{-1}$	0.0288**	0.0142**	0.0030	0.0030	0.0028	0.0028
	(0.0032)	(0.0030)	(0.0032)	(0.0032)	(0.0034)	(0.0034)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	No	No	No	Yes	Yes
Obs.	10834	10834	10834	10834	10834	10834
Firms	1733	1733	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(K_{-1})$ is instrumented with the following IVs: $\Delta ln(K_{-3})$.

Table SM18: Relation between firm size (S) and average sales ratio - new vs existing products. Sample of firms with variable portfolio. Dependent variable is $ln(1 + R^{in})$

	OLS	FE	FD-2SLS	FD-GMM	FD-2SLS-ATT	FD-GMM-ATT
$ln(1 + R^{in}_{-1})$	0.1267**	−0.1063**	−0.0132	−0.0015	−0.0140	−0.0022
	(0.0168)	(0.0159)	(0.0311)	(0.0294)	(0.0320)	(0.0280)
$ln(S_{-1})$	−0.0048**	−0.0642**	−0.1290**	−0.1288**	−0.1309**	−0.1307**
	(0.0011)	(0.0084)	(0.0133)	(0.0133)	(0.0137)	(0.0138)
$ln(K_{-1})$	0.0201**	0.0471**	0.0866**	0.0875**	0.0743**	0.0750**
	(0.0040)	(0.0143)	(0.0233)	(0.0233)	(0.0250)	(0.0250)
$Age = 11 - 20$	−0.0061	−0.0021	−0.0077	−0.0082	−0.0058	−0.0063
	(0.0091)	(0.0142)	(0.0197)	(0.0197)	(0.0199)	(0.0203)
$Age = 21 - 50$	0.0015	0.0082	−0.0060	−0.0039	−0.0038	−0.0016
	(0.0082)	(0.0339)	(0.0332)	(0.0332)	(0.0338)	(0.0334)
$Age > 50$	−0.0383**	0.0333	−0.0131	−0.0076	−0.0123	−0.0067
	(0.0090)	(0.0390)	(0.0434)	(0.0432)	(0.0435)	(0.0429)
k^{in} (%)	0.0009*	0.0007*	0.0007*	0.0007*	0.0007*	0.0007*
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
k^{in}_{-1} (%)	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
k^{out} (%)	0.0001	−0.0002	−0.0005	−0.0005	−0.0006	−0.0006*
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$newmol$	0.1911**	0.1734**	0.1728**	0.1728**	0.1731**	0.1731**
	(0.0107)	(0.0112)	(0.0123)	(0.0123)	(0.0124)	(0.0124)
$newmol_{-1}$	−0.0073	0.0187*	0.0072	0.0044	0.0083	0.0055
	(0.0084)	(0.0088)	(0.0105)	(0.0102)	(0.0105)	(0.0097)
$newmol_{-2}$	0.0037	−0.0060	0.0052	0.0049	0.0058	0.0056
	(0.0074)	(0.0080)	(0.0092)	(0.0092)	(0.0092)	(0.0091)
$ln(atcmain)_{-1}$	−0.0280**	−0.0120	0.1232**	0.1299**	0.1239**	0.1306**
	(0.0087)	(0.0246)	(0.0399)	(0.0395)	(0.0404)	(0.0353)
$atcd_{-1}$	−0.0059	−0.0285**	−0.0498**	−0.0483**	−0.0499**	−0.0484**
	(0.0093)	(0.0108)	(0.0117)	(0.0116)	(0.0120)	(0.0118)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	No	No	No	Yes	Yes
Obs.	10834	10834	10834	10834	10834	10834
Firms	1733	1733	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2SLS and GMM models the variable $ln(1 + R^{in}_{-1})$ is instrumented with the following IVs: $\Delta ln(1 + R^{in}_{-2})$, $\Delta ln(1 + R^{in}_{-3})$.

Table SM19: Relation between firm size (S) and average sales ratio - old vs existing products. Sample of firms with variable portfolio. Dependent variable is $ln(1 + R^{out})$

	OLS	FE	FD-2S	FD-GMM	FD-2S-ATT	FD-GMM-ATT
$ln(1 + R^{out}_{-1})$	0.0432**	−0.1265**	0.0006	−0.0053	0.0007	−0.0055
	(0.0134)	(0.0123)	(0.0274)	(0.0246)	(0.0272)	(0.0263)
$ln(S_{-1})$	−0.0040**	−0.0051	0.0144	0.0148*	0.0129	0.0133
	(0.0005)	(0.0036)	(0.0074)	(0.0074)	(0.0073)	(0.0073)
$ln(K_{-1})$	0.0049**	−0.0020	−0.0175	−0.0185	−0.0245*	−0.0256*
	(0.0015)	(0.0060)	(0.0103)	(0.0101)	(0.0104)	(0.0102)
$Age = 11 - 20$	−0.0030	0.0019	0.0092	0.0099	0.0108	0.0115
	(0.0039)	(0.0065)	(0.0115)	(0.0114)	(0.0113)	(0.0115)
$Age = 21 - 50$	−0.0063	−0.0018	0.0109	0.0115	0.0129	0.0134
	(0.0033)	(0.0097)	(0.0149)	(0.0149)	(0.0147)	(0.0149)
$Age > 50$	−0.0139**	−0.0056	0.0076	0.0082	0.0080	0.0086
	(0.0036)	(0.0127)	(0.0180)	(0.0180)	(0.0180)	(0.0182)
k^{in} (%)	0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
k^{in}_{-1} (%)	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
k^{out} (%)	0.0031**	0.0030**	0.0033**	0.0033**	0.0033**	0.0033**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$newmol$	−0.0051*	−0.0015	−0.0021	−0.0020	−0.0020	−0.0019
	(0.0023)	(0.0029)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
$newmol_{-1}$	−0.0044	−0.0015	−0.0018	−0.0019	−0.0013	−0.0014
	(0.0026)	(0.0026)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
$newmol_{-2}$	−0.0035	−0.0000	−0.0009	−0.0007	−0.0006	−0.0004
	(0.0024)	(0.0029)	(0.0037)	(0.0036)	(0.0037)	(0.0037)
$ln(atcmain)_{-1}$	−0.0194**	−0.0447**	−0.1020**	−0.1014**	−0.1011**	−0.1004**
	(0.0026)	(0.0096)	(0.0149)	(0.0148)	(0.0148)	(0.0147)
$atcd_{-1}$	0.0132**	0.0049	−0.0097	−0.0096	−0.0096	−0.0095
	(0.0038)	(0.0044)	(0.0055)	(0.0055)	(0.0055)	(0.0053)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	No	No	No	Yes	Yes
Obs.	10834	10834	10834	10834	10834	10834
Firms	1733	1733	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(1+R^{out}_{-1})$ is instrumented with the following IVs: $\Delta ln(1 + R^{out}_{-2})$, $\Delta ln(1 + R^{out}_{-3})$.

Table SM20: Relation between firm size (S) and sales growth rate of stable products. Sample of firms with variable portfolio. Dependent variable is g_{S^*}

	OLS	FE	FD-2S	FD-GMM	FD-2S-ATT	FD-GMM-ATT
$ln(S_{-1})$	0.0209**	−0.1698**	−0.1965**	−0.2006**	−0.3162**	−0.3301**
	(0.0019)	(0.0139)	(0.0530)	(0.0511)	(0.0552)	(0.0542)
$Age = 11 - 20$	−0.0390*	−0.0618*	−0.0642*	−0.0645*	−0.0499	−0.0510
	(0.0169)	(0.0295)	(0.0318)	(0.0318)	(0.0316)	(0.0316)
$Age = 21 - 50$	−0.0107	−0.0536	−0.0629	−0.0636	−0.0463	−0.0496
	(0.0150)	(0.0429)	(0.0528)	(0.0527)	(0.0508)	(0.0488)
$Age > 50$	−0.0481**	−0.0272	−0.0754	−0.0760	−0.0630	−0.0658
	(0.0156)	(0.0492)	(0.0592)	(0.0592)	(0.0574)	(0.0553)
k^{in} (%)	−0.0001	−0.0004*	−0.0004	−0.0004*	−0.0005*	−0.0005*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
k^{in}_{-1} (%)	0.0013**	0.0010*	0.0009*	0.0009*	0.0009*	0.0009*
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
k^{out} (%)	−0.0036**	0.0000	0.0009	0.0009	0.0002	0.0001
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)
$newmol$	−0.0007	−0.0039	−0.0052	−0.0053	−0.0042	−0.0044
	(0.0086)	(0.0095)	(0.0091)	(0.0091)	(0.0090)	(0.0089)
$newmol_{-1}$	0.0528**	0.0613**	0.0520**	0.0520**	0.0553**	0.0553**
	(0.0105)	(0.0119)	(0.0117)	(0.0117)	(0.0116)	(0.0114)
$newmol_{-2}$	0.0138	0.0305**	0.0340**	0.0337**	0.0385**	0.0377**
	(0.0077)	(0.0091)	(0.0091)	(0.0091)	(0.0089)	(0.0088)
$ln(atcmain)_{-1}$	0.0027	−0.1010**	−0.2580**	−0.2568**	−0.2347**	−0.2310**
	(0.0071)	(0.0245)	(0.0365)	(0.0363)	(0.0345)	(0.0331)
$atcd_{-1}$	0.0416**	0.0384**	0.0443**	0.0447**	0.0396**	0.0404**
	(0.0122)	(0.0128)	(0.0131)	(0.0130)	(0.0122)	(0.0120)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	No	No	No	Yes	Yes
Obs.	10834	10834	10834	10834	10834	10834
Firms	1733	1733	1733	1733	1733	1733

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. In 2S and GMM models the variable $ln(S_{-1})$ is instrumented with the following IVs: $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$.

Table SM21: Relation between firm size (S) and sales growth rate of stable products (observed in all periods). Sample of firms with variable portfolio. Dependent variable is g_{S^*}, where product flows have been removed from S^*. S^* is also decomposed between products exposed and non-exposed to cannibalization. Exposure is defined by same ATC3

|	Exposed & non-exposed		Exposed		Non-exposed	
	FD-GMM	FD-GMM-ATT	FD-GMM	FD-GMM-ATT	FD-GMM	FD-GMM-ATT
$ln(S_{-1})$	−0.1315	−0.2101*	−0.4567**	−0.4630**	−0.0309	−0.1000
	(0.0877)	(0.1025)	(0.1658)	(0.1652)	(0.0888)	(0.1052)
$Age = 11-20$	−0.0376	−0.0309	0.0165	0.0193	−0.0664	−0.0587
	(0.0574)	(0.0567)	(0.0994)	(0.0994)	(0.0514)	(0.0505)
$Age = 21-50$	−0.0087	−0.0028	−0.0006	0.0040	−0.0338	−0.0272
	(0.0701)	(0.0692)	(0.1186)	(0.1195)	(0.0683)	(0.0668)
$Age > 50$	−0.0399	−0.0355	0.0367	0.0375	−0.0646	−0.0585
	(0.0761)	(0.0752)	(0.1268)	(0.1281)	(0.0749)	(0.0734)
k^{in} (%)	−0.0002	−0.0002	−0.0001	−0.0000	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0006)	(0.0006)	(0.0002)	(0.0002)
k^{in}_{-1} (%)	−0.0002	−0.0003	−0.0004	−0.0004	−0.0003	−0.0004
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0003)
k^{out} (%)	−0.0006	−0.0012*	0.0008	0.0004	−0.0011	−0.0015*
	(0.0006)	(0.0006)	(0.0015)	(0.0015)	(0.0006)	(0.0006)
$newmol$	0.0220	0.0228	0.0177	0.0185	0.0232	0.0238*
	(0.0142)	(0.0141)	(0.0212)	(0.0213)	(0.0119)	(0.0117)
$newmol_{-1}$	0.0187	0.0212	0.0199	0.0202	0.0126	0.0154
	(0.0153)	(0.0153)	(0.0195)	(0.0195)	(0.0153)	(0.0153)
$newmol_{-2}$	0.0317*	0.0350*	0.0288	0.0289	0.0213	0.0245
	(0.0141)	(0.0141)	(0.0217)	(0.0218)	(0.0133)	(0.0133)
$ln(atcmain)_{-1}$	−0.0897	−0.0754	0.0510	0.0517	−0.0748	−0.0639
	(0.0473)	(0.0464)	(0.0659)	(0.0658)	(0.0502)	(0.0494)
$atcd_{-1}$	0.0374*	0.0347*	0.0096	0.0099	0.0396*	0.0370*
	(0.0172)	(0.0169)	(0.0216)	(0.0216)	(0.0166)	(0.0163)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × IMR	No	Yes	No	Yes	No	Yes
Obs.	9984	9984	4840	4840	9449	9449
Firms	1534	1534	700	700	1453	1453

Notes: * significant 5%, ** significant 1%. In models correcting for attrition, standard errors are bootstrapped with 5000 replications , otherwise they are firm-clustered robust. The endogenous variable is instrumented with $\Delta ln(S_{-2})$ in all cases. See Table SM32 for diagnostics test.

Figure SM5: Cannibalization effects between firm's new and existing products in same ATC3 class.

(a) Large firms

(b) Small firms

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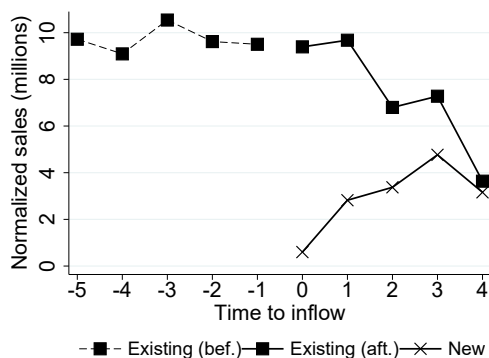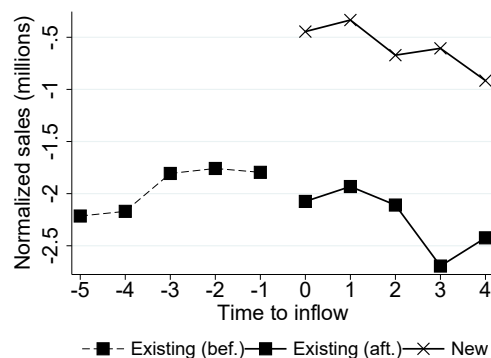
SM5. Diagnostic tests of IV model estimates

Table SM22: Diagnostic tests of FD-GMM-ATT estimates of size-growth equations (see Table 4)

		Stable portfolio	Variable portfolio
	Excluded Instruments:	$\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$, $\Delta ln(S_{-4})$	$\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$, $\Delta ln(S_{-4})$
1	Attrition:	$\chi^2(7) =23.3$ ($p =0.002$)	$\chi^2(7) =36.6$ ($p =0.000$)
2	Autocorrelation		
	AR(1):	$z =-3.9$ ($p =0.000$)	$z =-5$ ($p =0.000$)
	AR(2):	$z =0.1$ ($p =0.902$)	$z =-1.3$ ($p =0.191$)
	AR(3):	$z =0.6$ ($p =0.527$)	$z =-1.6$ ($p =0.112$)
3	IVs relevance (1st stage):	$F(3, 439) =11.9$ ($p =0.000$)	$F(3, 1732) =108.9$ ($p =0.000$)
4	IVs underidentification (all)	$\chi^2(3) =22.4$ ($p =0.000$)	$\chi^2(3) =175$ ($p =0.000$)
5	IVs underidentification		
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) =13.9$ ($p =0.000$)	$\chi^2(1) =151.4$ ($p =0.000$)
	IV: $\Delta ln(S_{-3})$	$\chi^2(1) =9.7$ ($p =0.002$)	$\chi^2(1) =11.4$ ($p =0.001$)
	IV: $\Delta ln(S_{-4})$	$\chi^2(1) =0.7$ ($p =0.396$)	$\chi^2(1) =5.6$ ($p =0.018$)
6	IVs overidentification (all)	$\chi^2(2) =0.3$ ($p =0.844$)	$\chi^2(2) =3.6$ ($p =0.169$)
7	IVs overidentification		
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) =0.3$ ($p =0.569$)	$\chi^2(1) =2.1$ ($p =0.151$)
	IV: $\Delta ln(S_{-3})$	$\chi^2(1) =0.3$ ($p =0.586$)	$\chi^2(1) =0.1$ ($p =0.776$)
	IV: $\Delta ln(S_{-4})$	$\chi^2(1) =0.000$ ($p =0.888$)	$\chi^2(1) =3.2$ ($p =0.071$)

Notes: See Notes to Table 3.

Table SM23: Diagnostic tests of FD-GMM-ATT estimates of size-growth equations (see Table SM15)

		Stable portfolio	Variable portfolio
	Excluded Instruments:	$\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$	$\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$
1	Attrition:	$\chi^2(7) =22$ ($p =0.003$)	$\chi^2(7) =40.1$ ($p =0.000$)
2	Autocorrelation		
	AR(1):	$z =-3.5$ ($p =0.000$)	$z =-4.5$ ($p =0.000$)
	AR(2):	$z =0.1$ ($p =0.915$)	$z =-1.1$ ($p =0.268$)
	AR(3):	$z =0.6$ ($p =0.526$)	$z =-1.5$ ($p =0.144$)
3	IVs relevance (1st stage):	$F(2, 439) =15.5$ ($p =0.000$)	$F(2, 1732) =142.6$ ($p =0.000$)
4	IVs underidentification (all)	$\chi^2(2) =20.7$ ($p =0.000$)	$\chi^2(2) =163.3$ ($p =0.000$)
5	IVs underidentification		
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) =14.7$ ($p =0.000$)	$\chi^2(1) =160$ ($p =0.000$)
	IV: $\Delta ln(S_{-3})$	$\chi^2(1) =11.2$ ($p =0.001$)	$\chi^2(1) =17$ ($p =0.000$)
6	IVs overidentification (all)	$\chi^2(1) =0.3$ ($p =0.573$)	$\chi^2(1) =0.3$ ($p =0.577$)
7	IVs overidentification		
	IV: $\Delta ln(S_{-2})$	.	.
	IV: $\Delta ln(S_{-3})$	.	.

Notes: See Notes to Table 3. Remark that the overidentification test for individual IVs cannot be performed in this case, because with only two instruments the equation without the tested instrument is just-identified.

Table SM24: Diagnostic tests of FD-GMM estimates of size-growth equations in K (see Table 6)

Excluded Instruments (3): $\Delta ln(K_{-3})$, $\Delta ln(K_{-4})$ $\Delta ln(S_{-2})$

1	Attrition:	$\chi^2(7) =6.3$ ($p =0.506$)
2	Autocorrelation	
	AR(1):	$z =-5.5$ ($p =0.000$)
	AR(2):	$z =-1.3$ ($p =0.188$)
	AR(3):	$z =-1.6$ ($p =0.109$)
3	IVs relevance (1st stage):	$F(3,1732) =45.1$ ($p =0.000$)
4	IVs underidentification (all)	$\chi^2(3) =105.3$ ($p =0.000$)
5	IVs underidentification	
	IV: $\Delta ln(K_{-3})$	$\chi^2(1) =7.3$ ($p =0.007$)
	IV: $\Delta ln(K_{-4})$	$\chi^2(1) =16$ ($p =0.000$)
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) =74.5$ ($p =0.000$)
6	IVs overidentification (all)	$\chi^2(2) =2.6$ ($p =0.27$)
7	IVs overidentification	
	IV: $\Delta ln(K_{-3})$	$\chi^2(1) =0.4$ ($p =0.544$)
	IV: $\Delta ln(K_{-4})$	$\chi^2(1) =1.9$ ($p =0.168$)
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) =2.3$ ($p =0.133$)

Notes: See Notes to Table 3.

Table SM25: Diagnostic tests of FD-GMM estimates of models for inflow rate (see Table SM16)

Excluded Instruments (3): $\Delta ln(K_{-3})$, $\Delta ln(K_{-4})$ $\Delta ln(S_{-2})$

1	Attrition:	$\chi^2(7) =5.1$ ($p =0.642$)
2	Autocorrelation	
	AR(1):	$z =-7.8$ ($p =0.000$)
	AR(2):	$z =-0.3$ ($p =0.73$)
	AR(3):	$z =-1.6$ ($p =0.121$)
3	IVs relevance (1st stage):	$F(3,1732) =45.1$ ($p =0.000$)
4	IVs underidentification (all)	$\chi^2(3) =105.3$ ($p =0.000$)
5	IVs underidentification	
	IV: $\Delta ln(K_{-3})$	$\chi^2(1) =7.3$ ($p =0.007$)
	IV: $\Delta ln(K_{-4})$	$\chi^2(1) =16$ ($p =0.000$)
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) =74.5$ ($p =0.000$)
6	IVs overidentification (all)	$\chi^2(2) =2.1$ ($p =0.345$)
7	IVs overidentification	
	IV: $\Delta ln(K_{-3})$	$\chi^2(1) =2$ ($p =0.162$)
	IV: $\Delta ln(K_{-4})$	$\chi^2(1) =0.4$ ($p =0.55$)
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) =1.8$ ($p =0.177$)

Notes: See Notes to Table 3.

Table SM26: Diagnostic tests of FD-GMM estimates of models for outflow rate (see Table SM17)

Excluded Instruments (1): $\Delta ln(K_{-3})$

1	Attrition:	$\chi^2(7) =4.5$ ($p =0.715$)
2	Autocorrelation	
	AR(1):	$z =-5.3$ ($p =0.000$)
	AR(2):	$z =-0.8$ ($p =0.422$)
	AR(3):	$z =-1.6$ ($p =0.111$)
3	IVs relevance (1st stage):	$F(1,1732) =17.5$ ($p =0.000$)
4	IVs underidentification (all)	$\chi^2(1) =18.8$ ($p =0.000$)
5	IVs underidentification	
	IV: $\Delta ln(K_{-3})$	.
6	IVs overidentification (all)	.
7	IVs overidentification	
	IV: $\Delta ln(K_{-3})$	.

Notes: See Notes to Table 3. Remark that the overidentification test cannot be performed in this case, because the model is just-identified.

Table SM27: Diagnostic tests of FD-GMM estimates of models for average sales ratio - new vs existing products (see Table SM18)

		Excluded Instruments (2): $\Delta ln(1 + R^{in}_{-2})$, $\Delta ln(1 + R^{in}_{-3})$
1	Attrition:	$\chi^2(7) = 13.6$ ($p = 0.06$)
2	Autocorrelation	
	AR(1):	$z = -12.3$ ($p = 0.000$)
	AR(2):	$z = 0.000$ ($p = 0.993$)
	AR(3):	$z = -0.4$ ($p = 0.681$)
3	IVs relevance (1st stage):	$F(2, 1732) = 937.8$ ($p = 0.000$)
4	IVs underidentification (all)	$\chi^2(2) = 217.9$ ($p = 0.000$)
5	IVs underidentification	
	IV: $\Delta ln(1 + R^{in}_{-2})$	$\chi^2(1) = 204.6$ ($p = 0.000$)
	IV: $\Delta ln(1 + R^{in}_{-3})$	$\chi^2(1) = 192.9$ ($p = 0.000$)
6	IVs overidentification (all)	$\chi^2(1) = 1.4$ ($p = 0.242$)
7	IVs overidentification	
	IV: $\Delta ln(1 + R^{in}_{-2})$	.
	IV: $\Delta ln(1 + R^{in}_{-3})$	.

Notes: See Notes to Table 3. Remark that the overidentification test for individual IVs cannot be performed in this case, because with only two instruments the equation without the tested instrument is just-identified.

Table SM28: Diagnostic tests of FD-GMM estimates of models for average sales ratio - old vs existing products (see Table SM19)

		Excluded Instruments (2): $\Delta ln(1 + R^{out}_{-2})$, $\Delta ln(1 + R^{out}_{-3})$
1	Attrition:	$\chi^2(7) = 13.8$ ($p = 0.055$)
2	Autocorrelation	
	AR(1):	$z = -6.8$ ($p = 0.000$)
	AR(2):	$z = -1.4$ ($p = 0.176$)
	AR(3):	$z = 0.8$ ($p = 0.419$)
3	IVs relevance (1st stage):	$F(2, 1732) = 491.2$ ($p = 0.000$)
4	IVs underidentification (all)	$\chi^2(2) = 69.9$ ($p = 0.000$)
5	IVs underidentification	
	IV: $\Delta ln(1 + R^{out}_{-2})$	$\chi^2(1) = 69.2$ ($p = 0.000$)
	IV: $\Delta ln(1 + R^{out}_{-3})$	$\chi^2(1) = 54.1$ ($p = 0.000$)
6	IVs overidentification (all)	$\chi^2(1) = 0.2$ ($p = 0.624$)
7	IVs overidentification	
	IV: $\Delta ln(1 + R^{out}_{-2})$	.
	IV: $\Delta ln(1 + R^{out}_{-3})$	.

Notes: See Notes to Table 3. Remark that the overidentification test for individual IVs cannot be performed in this case, because with only two instruments the equation without the tested instrument is just-identified.

Table SM29: Diagnostic tests of FD-GMM-ATT estimates of models for sales growth rate of stable products (see Table SM20)

		Excluded Instruments (2): $\Delta ln(S_{-2})$, $\Delta ln(S_{-3})$
1	Attrition:	$\chi^2(7) = 52.5$ ($p = 0.000$)
2	Autocorrelation	
	AR(1):	$z = -5.9$ ($p = 0.000$)
	AR(2):	$z = 0.9$ ($p = 0.392$)
	AR(3):	$z = -1.5$ ($p = 0.141$)
3	IVs relevance (1st stage):	$F(2, 1732) = 142.6$ ($p = 0.000$)
4	IVs underidentification (all)	$\chi^2(2) = 163.3$ ($p = 0.000$)
5	IVs underidentification	
	IV: $\Delta ln(S_{-2})$	$\chi^2(1) = 160$ ($p = 0.000$)
	IV: $\Delta ln(S_{-3})$	$\chi^2(1) = 17$ ($p = 0.000$)
6	IVs overidentification (all)	$\chi^2(1) = 0.7$ ($p = 0.399$)
7	IVs overidentification	
	IV: $\Delta ln(S_{-2})$	.
	IV: $\Delta ln(S_{-3})$	.

Notes: See Notes to Table 3. Remark that the overidentification test for individual IVs cannot be performed in this case, because with only two instruments the equation without the tested instrument is just-identified.

Table SM30: Diagnostic tests of model estimates for average sales ratio - new vs existing products (see Table 9)

		NMC	NMC & EMC-EMKT-BRN
	Estimator:	FD-GMM	FD-GMM-ATT
	Excluded Instruments:	$\Delta ln(1+R^{in}_{-2}), \Delta ln(1+R^{in}_{-3})$	$\Delta ln(1+R^{in}_{-2}), \Delta ln(1+R^{in}_{-3})$
1	Attrition:	$\chi^2(7) = 7.9$ ($p = 0.343$)	$\chi^2(7) = 20.9$ ($p = 0.004$)
2	Autocorrelation		
	AR(1):	$z = -7.5$ ($p = 0.000$)	$z = -10.2$ ($p = 0.000$)
	AR(2):	$z = 1$ ($p = 0.334$)	$z = 1.2$ ($p = 0.214$)
	AR(3):	$z = -0.2$ ($p = 0.867$)	$z = -1.5$ ($p = 0.122$)
3	IVs relevance (1st stage):	$F(2, 1732) = 445.4$ ($p = 0.000$)	$F(2, 1732) = 922.8$ ($p = 0.000$)
4	IVs underidentification (all)	$\chi^2(2) = 67.4$ ($p = 0.000$)	$\chi^2(2) = 142.5$ ($p = 0.000$)
5	IVs underidentification		
	IV: $\Delta ln(1+R^{in}_{-2})$	$\chi^2(1) = 66.8$ ($p = 0.000$)	$\chi^2(1) = 141.3$ ($p = 0.000$)
	IV: $\Delta ln(1+R^{in}_{-3})$	$\chi^2(1) = 63$ ($p = 0.000$)	$\chi^2(1) = 128.4$ ($p = 0.000$)
6	IVs overidentification (all)	$\chi^2(1) = 2.3$ ($p = 0.132$)	$\chi^2(1) = 0.5$ ($p = 0.487$)
7	IVs overidentification		
	IV: $\Delta ln(1+R^{in}_{-2})$	.	.
	IV: $\Delta ln(1+R^{in}_{-3})$	.	.

Notes: See Notes to Table 3. Remark that the overidentification test for individual IVs cannot be performed in this case, because with only two instruments the equation without the tested instrument is just-identified.

Table SM31: Diagnostic tests of model estimates for sales growth rate of stable products (see Table 10)

		All stable products	Exposed	Non-exposed
	Estimator:	FD-GMM-ATT	FD-GMM	FD-GMM
	Excluded Instruments:	$\Delta ln(S_{-2})$	$\Delta ln(S_{-2})$	$\Delta ln(S_{-2})$
1	Attrition:	$\chi^2(7) =18.3$ ($p =0.011$)	$\chi^2(7) =8$ ($p =0.328$)	$\chi^2(7) =13.4$ ($p =0.063$)
2	Autocorrelation			
	AR(1):	$z =-3.9$ ($p =0.000$)	$z =-3.3$ ($p =0.001$)	$z =-4.1$ ($p =0.000$)
	AR(2):	$z =-1.9$ ($p =0.057$)	$z =-1.8$ ($p =0.071$)	$z =-1.1$ ($p =0.26$)
	AR(3):	$z =0.1$ ($p =0.952$)	$z =0.9$ ($p =0.37$)	$z =0.4$ ($p =0.726$)
3	IVs relevance (1st stage):	$F(1, 1533) =217.7$ ($p =0.000$)	$F(1, 655) =132.9$ ($p =0.000$)	$F(1, 1468) =268.9$ ($p =0.000$)
4	IVs underidentification (all)	$\chi^2(1) =145.3$ ($p =0.000$)	$\chi^2(1) =60.3$ ($p =0.000$)	$\chi^2(1) =164.5$ ($p =0.000$)
5	IVs underidentification IV: $\Delta ln(S_{-2})$	$\chi^2(1) =145.3$ ($p =0.000$)	$\chi^2(1) =60.3$ ($p =0.000$)	$\chi^2(1) =164.5$ ($p =0.000$)
6	IVs overidentification (all)	.	.	.
7	IVs overidentification IV: $\Delta ln(S_{-2})$	.	.	.

Notes: See Notes to Table 3. Remark that overidentification tests cannot be performed with one instrument.

Table SM32: Diagnostic tests of model estimates for sales growth rate of stable products (see Table SM21)

		All stable products	Exposed	Non-exposed
	Estimator:	FD-GMM-ATT	FD-GMM	FD-GMM
	Excluded Instruments:	$\Delta ln(S_{-2})$	$\Delta ln(S_{-2})$	$\Delta ln(S_{-2})$
1	Attrition:	$\chi^2(7) = 18.3$ ($p = 0.011$)	$\chi^2(7) = 5.2$ ($p = 0.635$)	$\chi^2(7) = 13.9$ ($p = 0.053$)
2	Autocorrelation			
	AR(1):	$z = -3.9$ ($p = 0.000$)	$z = -3.3$ ($p = 0.001$)	$z = -4.1$ ($p = 0.000$)
	AR(2):	$z = -1.9$ ($p = 0.057$)	$z = -1.7$ ($p = 0.085$)	$z = -1.2$ ($p = 0.237$)
	AR(3):	$z = 0.1$ ($p = 0.952$)	$z = 0.7$ ($p = 0.512$)	$z = 0.3$ ($p = 0.735$)
3	IVs relevance (1st stage):	$F(1, 1533) = 217.7$ ($p = 0.000$)	$F(1, 699) = 143.5$ ($p = 0.000$)	$F(1, 1452) = 265.7$ ($p = 0.000$)
4	IVs underidentification (all)	$\chi^2(1) = 145.3$ ($p = 0.000$)	$\chi^2(1) = 66.1$ ($p = 0.000$)	$\chi^2(1) = 162.9$ ($p = 0.000$)
5	IVs underidentification IV: $\Delta ln(S_{-2})$	$\chi^2(1) = 145.3$ ($p = 0.000$)	$\chi^2(1) = 66.1$ ($p = 0.000$)	$\chi^2(1) = 162.9$ ($p = 0.000$)
6	IVs overidentification (all)	.	.	.
7	IVs overidentification IV: $\Delta ln(S_{-2})$	.	.	.

Notes: See Notes to Table 3. Remark that overidentification tests cannot be performed with one instrument.

SM6. Derivation of Equation 6

Equation 6 is derived as follows:

$$g_{\overline{S}} = ln\left(\overline{S}\right) - ln\left(\overline{S}_{-1}\right) = ln\left(\frac{S/K}{S_{-1}/K_{-1}}\right) = ln\left(S/S_{-1}\right) - g_K =$$

$$= ln\left(\frac{\left(S_{-1} - S^{out}\right)e^{g_{S^*}} + S^{in}}{S_{-1}}\right) - g_K = ln\left(e^{g_{S^*}} + \frac{S^{in}}{S_{-1}} - \frac{S^{out}}{S_{-1}}e^{g_{S^*}}\right) - g_K$$

$$= ln\left(e^{g_{S^*}} + \frac{S^{in}}{S_{-1}}\frac{K^{in}}{K^{in}}\frac{K_{-1}}{K_{-1}} - \frac{S^{out}}{S_{-1}}\frac{K^{out}}{K^{out}}\frac{K_{-1}}{K_{-1}}e^{g_{S^*}}\right) - g_K$$

$$= ln\left(e^{g_{s^*}} + R^{in}\kappa^{in} - R^{out}\kappa^{out}e^{g_{s^*}}\right) - g_K,$$

where we made use of the following equality: $S = S^* + S^{in} = S^{*1}e^{g_{S^*}} + S^{in} = (S_{-1} - S^{out})e^{g_{S^*}} + S^{in}$.