



Intangible investment and firm performance

Nathan Chappell and Adam Jaffe

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Author contact details

Adam Jaffe

Motu Economic and Public Policy Research, Te Pūnaha Matatini, Queensland University of Technology

adam.jaffe@motu.org.nz

Nathan Chappell

Motu Economic and Public Policy Research

nathan.chappell@motu.org.nz

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Motu Economic and Public Policy Research

PO Box 24390 info@motu.org.nz +64 4 9394250
Wellington www.motu.org.nz
New Zealand

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Abstract

We combine survey and administrative data for about 13,000 firms from 2005 to 2013 to study the inter-relationships among firm characteristics, intangible investment and firm performance. We find that firm size is associated with higher intangible investment, while firm age, very low competition ('captive market') and very high competition ('many competitors, none dominant') are associated with lower intangible investment. Relating intangible investment to subsequent firm performance, we find that higher investment is associated with higher labour and capital input and higher revenue, relative to what would otherwise have been predicted. We also find that higher investment is associated with higher firm-reported employee and customer satisfaction, but is not associated with higher productivity or profitability. While we cannot estimate a causal model, the evidence suggests that intangible investment is associated with firm strategies related to growth and possibly to 'soft' performance objectives, but not to productivity or profitability.

JEL codes

D22, D24, L21

Keywords

Intangible investment; productivity; firm performance; industrial policy

Summary haiku

It is hard to see
where intangibles take you.
Happy customers?

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1 Introduction

Policymakers and researchers frequently discuss the ‘puzzle’ of New Zealand’s poor productivity performance despite its institutions that seem conducive to growth. Popular explanations include low research and development (R&D) and small local markets that insulate firms from competitive pressure (de Serres et al., 2014). Others believe poor management practices play an important role. In practice, these phenomena are difficult to separate, as competition, management and R&D investment are all endogenous aspects of the overall economic system.

The possible importance of management and R&D in productivity is an aspect of a broader developing realization of the importance of intangible investment in firm performance (Corrado, et al, 2009; Corrado, et al, 2012; Bontempi and Mairesse, 2015). We can think of firms as having stocks of intangible capital of various kinds, in the form of knowledge about production possibilities, practices and procedures, strategies, organizational structures, etc. Intangible investment increases these stocks, just as traditional investment increases traditional capital such as machines and structures. And an increase in intangible capital should increase firm output and the productivity of labour, in a manner analogous to that resulting from increases in tangible capital. If we could measure the stocks of intangible capital, we could include them in estimating production functions for firms, and estimate their effect on output and their rates of return. But if we don’t include them in the production function, then their impact on output flows through to the “residual” or the productivity of the firm. This means that, in principle, observed differences in productivity could be due to underlying differences in the extent of intangible investment. Similarly, since we would expect firms to earn a return on their intangible investment, the profitability of the firm—measured in the traditional manner as profits relative to the value of traditional capital—should be increased by intangible investment.

An alternative view could be that firms engage in intangible investment (e.g. employee training, organizational restructuring, new product designs) in response to perceived weakness or threats to the business. While this possibility is not inconsistent with such investment having a productivity and profitability payoff, it suggests that observed investment might be concentrated in poorly performing firms, perhaps obscuring an underlying positive causal effect of intangible investment on productivity.¹

In this paper, we try to untangle the relationships among intangible investment, firm characteristics and environment, and firm performance, using firm-level survey data on

¹ By analogy, the building fires to which the most fire engines are sent are also the ones in which the largest amount of property damage occurs. It is likely that, holding constant the initial intensity of the fire, sending more engines *reduces* the amount of damage. But that relationship is obscured by the ‘reverse causality’ running from fire damage to number of engines.

intangible investment linked to administrative and tax records of firm performance and characteristics. We examine both the characteristics of firms that are associated with intangible investment, and what firm performance looks like subsequent to such investment.

To preview our findings, the results suggest that, comparing firms within a narrowly defined industry, intangible investment is highest in larger firms, in younger firms, and in firms that face moderate competition in the marketplace. Contrary to the prediction from the simple version of the investment story, we find no evidence that higher intangible investment is associated with higher productivity or higher profitability. Subsequent to reporting intangible investment firms appear to increase spending on both capital and labour, and see an increase in deflated revenue, but the rates of increase of inputs and outputs are such that measured productivity and profitability do not increase. Consistent with this “growth without profit” picture, we find some evidence that intangible investment is associated with subsequent improvement in ‘soft’ aspects of firm performance such as firm-reported customer and employee satisfaction.

Because all of our variables are determined jointly by the decisions of the firm, it is very difficult to draw causal inferences regarding the empirical associations we have found. Nonetheless, we have sliced the data many different ways and found little evidence of intangible investment contributing *positively* to productivity in New Zealand. Further, we find no evidence that firms investing in intangibles are underperformers *before* undertaking the investment, so it appears unlikely that a positive investment effect is being concealed by a negative selection effect. Thus it appears that low intangible investment is a not a likely candidate for a large contribution to New Zealand’s relatively poor productivity performance. Rather, such investment appears to be associated with firm growth, and possibly improvement in firm performance along dimensions not captured by productivity statistics. The results do not allow us to say whether intangible investment causes firm growth, in the sense of being a choice available to any firm that wants to grow faster. But it is clearly associated with growth, suggesting that in at least some situations it is a necessary factor for growth.

2 Literature

Much of the previous literature on intangibles and firm performance focuses specifically on research and development (R&D). Griliches (1979) highlights the difficulties, both conceptual and empirical, in studying the impact of R&D on productivity growth, while Pakes and Griliches (1984) model the flow of intangible R&D investment into innovation output as measured by patents, finding their knowledge production function explains much of the between-firm variation in knowledge but little of the within-firm changes over time. Crepon et al. (1998)

develop a framework for looking at the determinants of R&D, how R&D contributes to innovation, and finally how innovation contributes to productivity. Their empirical results are consistent with the typical stylised facts: R&D increases with firm size, market share and diversification; innovation output increases with research effort and demand pull and technology indicators; and firm productivity increases with innovation output, even after controlling for the skill composition of labour.

More recently researchers have begun to look at intangible investment more broadly, as R&D is only one facet of intangible investment and is more relevant in some industries than others. Corrado et al. (2005) argue that intangible investment should be treated equivalently to tangible investment; it delays current production in order to increase future production. They group intangible capital into three broad categories that have gained traction in the literature: computerised information (primarily software and databases), innovative property (primarily R&D) and economic competencies (firm-specific resources including trained employees, brand names etc.). While caveating their imperfect data, they estimate intangible expenditure made up around 13 percent of GDP in the US in the late 1990s, and conclude that the only reason for not incorporating intangibles into the productivity framework should be a lack of data. They end with the hope that statistical agencies will work towards accurate intangible measures.

Corrado et al. (2009) build on their 2005 paper by incorporating intangibles into growth accounting, and find that output per hour in the non-farm business sector is 10–20 percent higher when intangibles are measured. Relatedly, Elnasri and Fox (2015) examine the presence and trends of intangibles in the Australian economy, finding the ratio of intangible to tangible investment increased from around 0.24 in 1974–75 to 0.36 in 2012–13.

These studies look at intangible investment at the macro level. Limited recent work has looked at intangibles at the firm level, though firm-level analysis is needed to uncover the determinants and consequences of intangible investment. Crass and Peters (2015) believe many of the within-industry differences in productivity can be explained by differences in intangible investment. Using survey data on German manufacturing and services firms, they find positive associations between firm productivity and their three measures of intangibles: innovative capital, human capital and branding capital. Bontempi and Mairesse (2015) use Italian firm-level data and find an output elasticity of overall intangible capital of 0.03–0.07. Furthermore, their data allow them to measure intangible expenditure as an investment, and they argue accounting standards that treat intangibles as costs tend to underestimate the true impact of intangibles on productivity.

Relatedly, Lin and Lo (2015) use data on panel of Taiwanese manufacturing firms and their expenditures on intangibles as measured by the acquisition of technology; purchasing of software and databases; marketing; employee training; and R&D. They present evidence of a

positive impact of intangible investment on productivity, with overall output elasticity of around 0.07. Finally, Montresor and Vezzani (2016) investigate the links between intangible investment and innovation by looking at a cross-section of European firms appearing in a 2013 multi-country survey. They conclude that developing intangibles internally rather than externally is conducive to innovation; that the amount invested is important for firms in manufacturing but not services; and that investing in ‘technological’ intangibles (R&D, software and design) fosters innovation more than non-technological intangibles (training, reputation/branding, and organisational/business processes).

A final strand of literature focuses on whether resources flow freely to firms that will use these resources productively. Balasubramanian and Sivadasan (2011) look at US firms and find increases in a firm’s patent stock is strongly associated with increases in size, while weaker evidence also suggests patenting is associated with an increase in the number of new products, capital intensity, skill intensity and productivity. Similarly, Andrews et al. (2014) look at firms across 23 OECD countries from 2003–2010 and find within-firm increases in patenting lead to increases in employment, capital, turnover and value added. They also use patent litigation data to construct an instrumental variable for the patent stock, and suggest the increase in real economic activity from patenting is causal. More broadly, Andrews and de Serres (2012) emphasise the importance of reallocating labour and capital to intangibles-investing firms, as such investment flourishes when supported by standard tangible investment. They conclude that some countries are more successful at channelling resources to their most productive use, and suggest future research should look at which policies are conducive to targeting resources to intangibles-investing firms.

Our study adds to this literature by looking at the links between broad intangible investment and activity across all industries in New Zealand. Using numerous indicators allows us to consider the numerous types of intangible investment including R&D, employee training and organisational restructuring, while the rich firm-level data allow us to describe in detail the characteristics of firms investing in intangibles, and what happens to them subsequently.

3 Data

3.1 Description of data and key variables

We use data from Statistics New Zealand’s Longitudinal Business Database (LBD), a firm-level longitudinal dataset containing administrative and survey data. Within the LBD, our main sample consists of firms that appear in at least one innovation module of the Business Operations Survey (BOS). The BOS is an annual survey of business performance and activities that is explicitly designed for longitudinal analysis (Fabling & Sanderson, 2016), though our key

intangible measures come from the innovation module, which appears every second year (2005, 2007, 2009, 2011 and 2013). For firms making at least one appearance in the innovation module, we then link administrative data from the given and additional years to create an unbalanced panel of firms, covering odd years in the period 2005–2013. This broad sample contains 12,603 firms and 52,983 firm-years, with the average firm appearing 4.2 times.

The following question contains our main measure of intangible investment:²

During the last 2 financial years, did this business do any of the following?

(Mark whether done to support innovation³; done though not to support innovation; not applicable; or don't know)

- Acquisition of computer hardware and software
- Implementing new business strategies or management techniques
- Organisational restructuring
- Design (e.g. industrial, graphic or fashion design)
- Market research
- Significant changes to marketing strategies
- Employee training
- Any research and development in the previous year⁴

From these indicators, our main measure of firm-level intangible investment is a simple intangibles index, which ranges in value from zero to one and is defined as

$$\text{intangibles index} = \frac{\text{no. of intangible activities engaged in}}{\text{no. of nonmissing intangible indicators}}$$

Hence we give equal weight to each intangible indicator, lacking strong theory on the different contributions of different types of intangible investment. Scaling by the number of non-missing intangible indicators ensures we don't infer that a firm has low intangible investment simply because it failed to answer a question, though we set the index to missing when a firm is missing four or more of the eight indicators.⁵ As an alternative, we perform principal component analysis on these eight indicators. Principal components analysis is a data-driven method for taking a large number of variables that are believed to capture overlapping aspects of the same phenomena, and reducing them to a smaller number of variables that

² The batch of questions also asks about acquiring of machinery and equipment; acquiring of other knowledge (e.g. licenses, patents or other intellectual property); and marketing the introduction of new goods or services. We exclude the first as it is a measure of tangible investment, and exclude the latter two as firms may see them as innovation-output indicators, rather than measures of intangible investment.

³ In 2005 the question only asks whether the activities were done to support innovation, meaning there is a systematic difference in our intangible measures between 2005 and the other years. Including year fixed effects in our later regression analysis helps to deal with this issue.

⁴ This question comes from the main 'business operations' module, and so asks whether R&D occurred in the previous year rather than in the previous two years. The question does not ask whether it is done to support innovation, though presumably fostering innovation is an inherent goal of R&D.

⁵ We assume the information in these answers is too messy and better dropped. This sets 12% of index values to be missing, though the majority (72%) of these changes come from the 2005 BOS, where non-innovating firms were steered away from the question on intangible investments.

capture most of the information present in the larger variable set. This reduces the eight responses to two constructed ‘component’ variables designed to capture the patterns of the eight original metrics. The correlation matrix of the intangibles indicators is presented in Appendix Table 1, while the weights of each indicator for the two components are shown in Appendix Table 2.⁶

A separate measure of intangible investment comes from the following question on intangibles-related expenditure⁷:

For the last financial year, please estimate this business’s combined expenditure on (the following) product development and related activities:

- Research and development
- Design
- Marketing and market research (for product development)
- Other expenditure related to product development (e.g. prototyping, trials, commercialisation)

In parts of our analysis we use these questions as another measure of a firm’s intangible investment, either by summing the total expenditure on these activities, or by using a dummy variable for whether a firm reports any expenditure.

In our analysis looking at firm-reported customer and employee satisfaction, we use the following questions from the main ‘business operations’ module⁸:

Is this business lower than competitors; on a par with competitors; higher than competitors; or don’t know for the each of the following?

- Costs
- Time taken to provide customers with goods or services
- Quality
- Flexibility or ability to make changes
- Customer satisfaction
- Employee satisfaction

We use the answers for customer and employee satisfaction as indicators of some kind of firm ‘success.’ We use the other answers to try to control for a generic tendency of the questionnaire respondent towards self-congratulation or overconfidence regarding the firm’s overall quality or performance. We construct a simple ‘confidence’ index as the average reported category for questions on relative costs; relative time to provide goods and services; relative quality of goods and services; and relative flexibility. We assign the number 1 to “lower” answers, 2 to “on par” answers and 3 to “higher than” answers. Hence the confidence index

⁶ In practice we only use the primary principal component, but present details on the second component for completion. In addition we use tetrachoric correlations between the underlying indicators, which estimate the correlation between two indicator variables, assuming that some normally-distributed latent variable underlies them

⁷ This question was not asked in 2005; our expenditure measures are missing for this year.

⁸ The question is slightly rephrased for clarity, but the substance and key words are unchanged.

takes on values between 1 and 3, where a value of 3 corresponds to answering “higher than” on all our control questions.

We combine these self-reported answers with administrative data from the LBD that show other firm characteristics and allow us to compute measures of firm performance. Firm size in a given year is measured by average monthly full-time equivalent (FTE) labour, using the FTE measure created by Fabling and Maré (2015a). Firm age is derived from the birth date of the firm, while a firm’s time-invariant industry comes from Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006 codes. At the broadest level there are 19 industry divisions, as listed in Appendix Table 3, though for much of our analysis we use the more detailed level 3 ANZSIC 2006 codes, which divide firms into 203 disaggregated industries.

Finally, productivity data comes from the work of Fabling and Maré (2015a). Their created dataset includes measures of gross output (deflated revenue); capital (deflated flow of capital services in a year); labour (using their adjusted FTE measure); and deflated intermediate consumption. These measures allow us to look at what happens to firms’ inputs and outputs after investing in intangibles, and also allow us to measure labour productivity as the ratio of value added to labour input. We also measure profitability as profit (value added minus total wages) per unit of capital. Finally, multi-factor productivity (MFP) is measured by the residuals in the Fabling and Maré (2015a) dataset, which come from translog gross-output production function regressions run separately for 39 industries. Hence these MFP measures are derived from the entire population of firms with available production data, and not only our sample of firms. This gives a more accurate picture of a firm’s productivity relative to the industry average.⁹

Our sample size decreases in analysis requiring these productivity data, from 12,603 firms making up 52,983 observations to 9,756 firms making up 28,236 observations. Partly this is because certain firms don’t meet the criteria or have implausible variation in inputs/outputs (see Fabling and Maré 2015a for details). Also, productivity data are not yet available for the 2013 March-year, which causes the loss of 9,936 observations.

3.2 Descriptive Statistics

Table 1 shows the proportion of firm-year observations that report engaging in different intangible activities, across the entire period. At the high end, over 70 percent of firm-years report acquiring computer-ware and training employees, while the least common activities are significant changes to marketing strategies (22 percent), design (20 percent) and R&D (12 percent).

⁹ We also use the alternate firm identifiers developed in Fabling (2011) to fix broken firm identifiers.

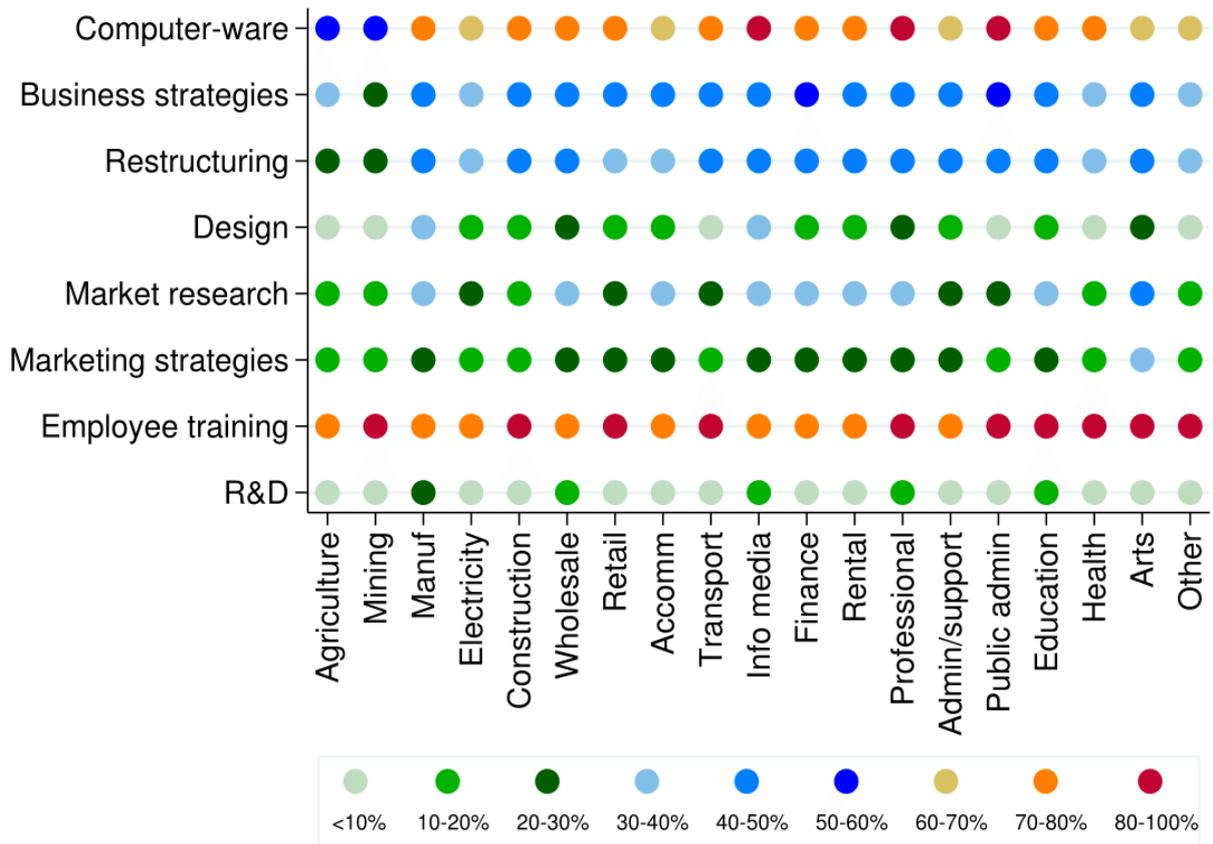
Table 1: Proportion of firm-years engaging in intangible activity

Intangible activity	Proportion of firm-years	Number of firm-years
Acquisition of computer hardware & software	0.723	27,354
Implementing new business strategies/management techniques	0.429	27,300
Organisational restructuring	0.413	27,315
Design	0.196	27,375
Market research	0.281	27,384
Significant changes to marketing strategies	0.218	27,375
Employee training	0.787	27,441
Research and development	0.123	30,804
Any intangible expenditure	0.327	23,142

Notes: Statistics are for the period (odd years) from March-year 2005 to March-year 2013. The first seven dummies measure whether the firm reports engaging in the activity in the previous two years, while the latter two are for the previous year, as outlined in the data section. Observation counts have been randomly rounded to base 3, for confidentiality reasons.

To provide more detail, Figure 1 presents, separately for each level 1 industry, the proportion of firm-years engaging in each of the eight intangible activities. The figure shows many similarities across industries. For example, in each industry the percentage of firm-years investing in employee training is greater than 70 percent, while the percentage reporting R&D is less than 30 percent. The differences that do exist are expected, and lend credibility to the intangible indicators as capturing real activities. Professional services firms have a relatively high likelihood of investment in all forms of intangibles, and agriculture firms relatively low. Manufacturing is the only industry with more than 20 percent of firms reporting R&D; the percentage doing restructuring is 10–20 percentage points lower in agriculture and mining than in most other industries; and investment in computer-ware is most prevalent in information media, administration/support services and public administration.

Figure 1: Proportion of firm-years engaging in each intangible activity, by industry



Notes: Full intangible activity descriptions are given in Section 3.1. Full industry descriptions are given in Appendix Table 3

Table 2 summarises the transitions into and out of intangible investment for firm-years in our sample. For a firm that was also in the innovation module two years previously, we report whether it adopted an intangible activity; dropped an intangible activity; or has the same status as last time (either doing the activity in both periods, or in neither period). There is some evidence of dynamism here; for most intangible indicators, between nine and 17 percent of firm-years report picking up an activity they were not engaged in two years ago, with similar but slightly higher proportions for dropping an activity.

Table 2: Proportion of firm-years transitioning into and out of intangibles

Intangible activity	Adopted	Dropped	Unchanged		Number of firm-years
	[0 → 1]	[1 → 0]	[1 → 1]	[0 → 0]	
New computer-ware	0.136	0.152	0.598	0.114	14,421
New business strategies	0.156	0.194	0.248	0.402	14,376
Organisational restructuring	0.167	0.187	0.235	0.411	14,391
Design	0.091	0.109	0.096	0.704	14,502
Market research	0.119	0.142	0.156	0.583	14,496
Changes to mkting strategies	0.119	0.136	0.085	0.660	14,496
Employee training	0.105	0.125	0.693	0.077	14,556
Research and development	0.058	0.054	0.078	0.810	16,767
Any intangible expenditure	0.110	0.114	0.208	0.537	12,219

Notes: Statistics are for the entire period (odd years) from March-year 2005 to March-year 2013. The first seven dummies measure whether the firm reports engaging in the activity in the previous two years, while the latter two are for the previous year, as outlined in the data section. Observation counts have been randomly rounded to base 3, for confidentiality reasons.

Table 3 summarises the distribution of the non-binary intangible measures, where the intangibles index is constructed from eight dummies as described in Section 3.1. The intangibles index distribution is fairly symmetric, with the mean close to the median. The median value of 0.375 corresponds to engaging in three intangible activities for a firm with no missing dummies ($0.375 * 8 = 3$). It is striking that, in contrast, the majority of firms do not report spending any money on the categories for product development and related activities: the median value of total intangible expenditure, and hence all the component categories, is \$0. Even the 90th percentile value is fairly low, with a value of \$150,200 for total intangible expenditure and between \$3,000 and \$20,000 for the component categories, though these values steeply increase when looking at the 95th percentile value.

How do we reconcile the fact that most firms say they engage in these activities, and yet a majority do not report any expenditure? One explanation is that firms may falsely report engaging in broadly defined activities that are viewed positively (e.g. employee training or market research), but tell the truth when it comes to the specifics of how much was spent. Alternatively, a firm may well know that it had activities fitting a given intangible definition, but not track expenditures connected to those activities. Hence in our analysis we focus on the broad intangible indicators and the constructed intangibles index, but use reported expenditure in robustness tests as an alternative measure of intangible investment.

Table 3: Distribution of self-reported intangible investment, all years

Statistic	Intangibles index (0-1)	Total intangibles expenditure	R&D expenditure	Design expenditure	Marketing expenditure	Other expenditure
mean	0.397	\$191,400	\$105,000	\$18,300	\$52,200	\$22,700
10th pctile	0.125	0	0	0	0	0
25th pctile	0.25	0	0	0	0	0
median	0.375	0	0	0	0	0
75th pctile	0.6	\$10,000	0	0	0	0
90th pctile	0.75	\$150,200	\$18,000	\$3,000	\$20,000	\$5,000
95th pctile	0.875	\$497,000	\$162,300	\$20,000	\$98,600	\$30,000
Number of firm-years	27,396	23,142	22,236	22,224	22,209	22,215

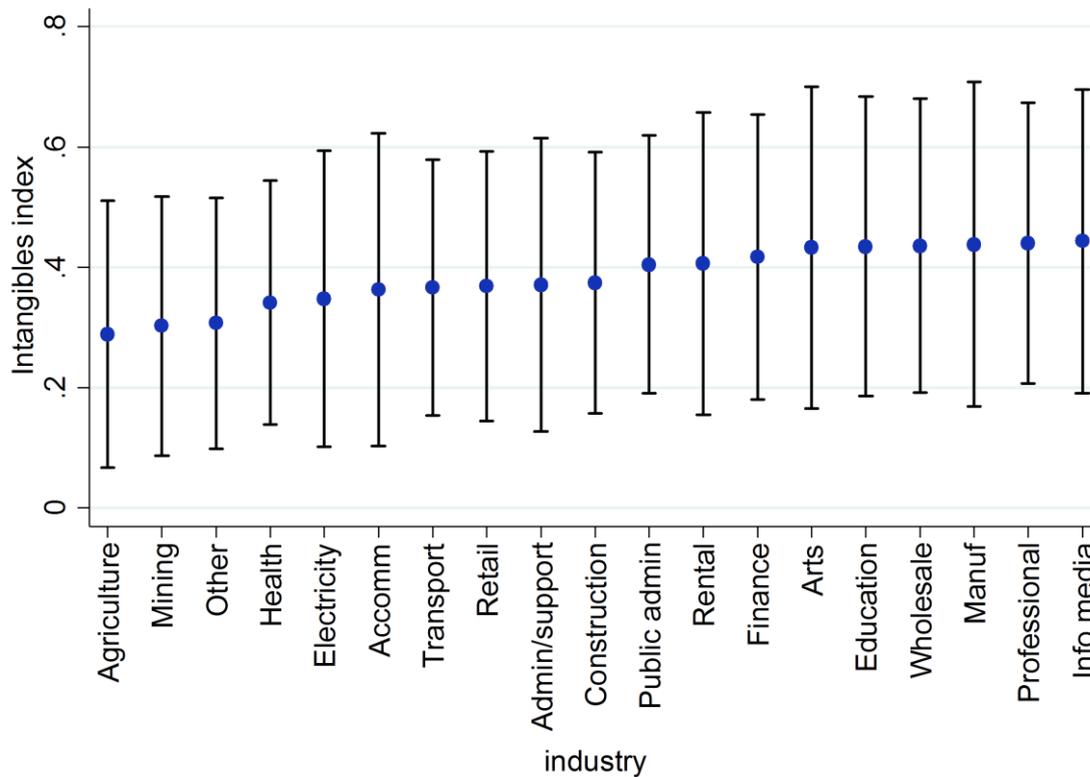
Notes: Statistics are for the entire period (odd years), from March-year 2005 to March-year 2013. Observation counts have been randomly rounded to base 3, for confidentiality reasons.

Figure 2 plots the average and one-standard-deviation spread of the intangibles index across all firm-years in the data, separately for each level 1 industry. The results show plausible variation in intangible investment across industries; firms in ‘information media’, ‘manufacturing’ or ‘professional, technical and scientific services’ have an average index value of over 0.4, corresponding to just over three out of eight activities when all questions are answered. In contrast, the average index for firms in ‘agriculture’ or ‘mining’ is around 0.3, corresponding to around two of the eight activities. The black bands show all values falling within one standard deviation of the mean for each industry, and show substantial variation in intangible investment for each industry. Indeed, a firm one standard deviation above the mean for the lowest average industry (agriculture) participates in more intangible investment categories than the average firm in the highest average industry (information media). Appendix Figure 1 plots the average principal component and one-standard-deviation bands by industry, and reveals a similar pattern.

A particular concern with the intangibles survey questions might be that with respect to any question of the form “did your firm do any of this activity”, larger firms are more likely to answer yes because the chances of any activity occurring somewhere in the firm are higher for a larger firm. To explore this issue, Appendix Table 4 presents a regression of firms’ intangible investment on past firm size and industry dummies. The differences across industries remain. Together with Figure 1, these show the BOS intangibles data are consistent with broad pre-existing notions of where such activity is likely. However, the large standard deviation bands

show the variation in firms' index values within an industry dominates the variation across industries.

Figure 2: Mean and spread of intangible investment, by industry



Notes: Figure 1 presents, as blue dots, the mean intangibles index for all firm-years by industry over the period 2005–2013. The black bands show all values falling with one standard deviation of the mean for each industry. Full industry descriptions are given in Appendix Table 3.

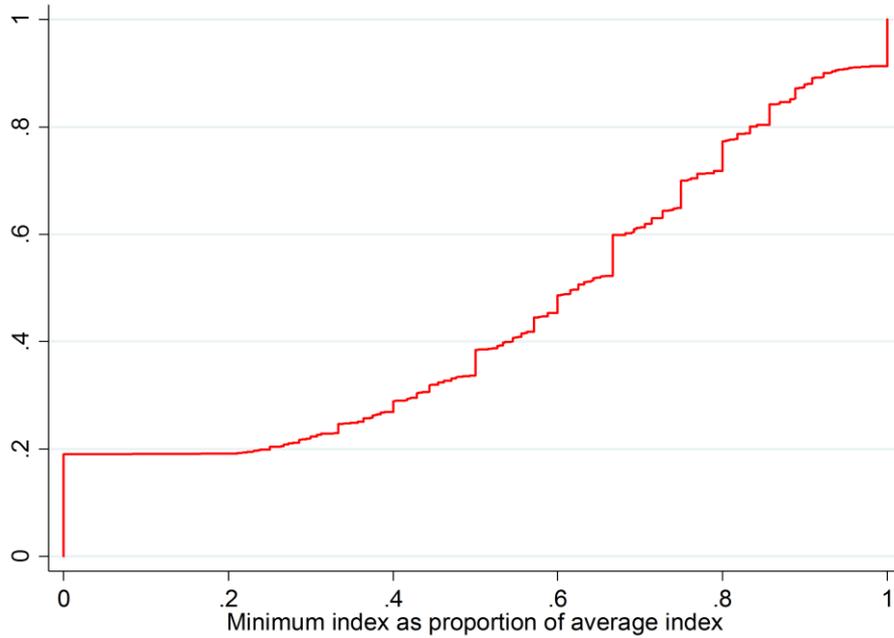
Finally, Figure 3 explores the variation in the intangibles index within firms. It shows the cumulative distribution function (CDF) of the ratio of each firm's minimum intangibles index to its average intangibles index, in panel A, and the ratio of the maximum intangibles index to the average, in panel B. The CDF shows the proportion of firms taking on a given value or lower, with the proportion ranging from 0–1 on the vertical axis. For example, panel A shows that only about half of the firms experience a year in which the index is less than 60% of its average value for that firm. Approximately 90 percent of firms experience a year in which the index is 90% of its average value or lower. Panel B shows that for about a quarter of the firms, the maximum value experienced by that firm is no more than 20% greater than the average, while about 85 percent of firms have a maximum ratio of 2 or less.¹⁰

¹⁰ The large ratio values of 3 and above in panel B are driven by firms with very low average index values, which blow up the proportion when used as the denominator.

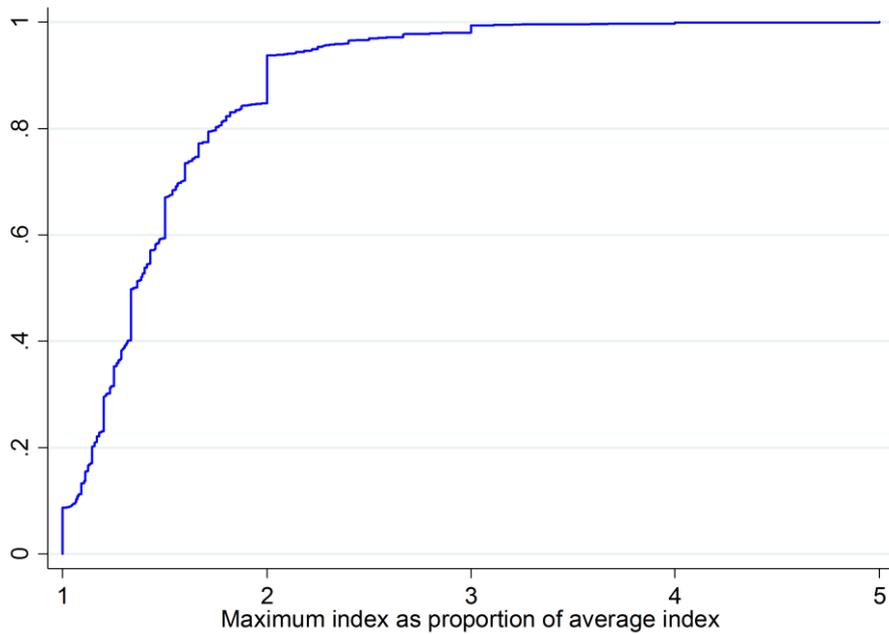
We interpret Figure 3 as showing a plausible degree of variation. We see neither a large number of firms with no variation over time, nor a large number with dramatic variations from year to year.

Figure 3: Variation in the intangibles index within firms

Panel A: CDF of minimum intangibles index as proportion of the average



Panel B: CDF of maximum intangibles index as proportion of the average



Notes: Figure 3 presents cumulative distribution functions of the minimum and maximum ratio of the intangibles index in a given year to the firm’s average intangibles index across all years. The sample is limited to firms appearing at least twice.

4 Results

4.1 Explaining intangible investment

Our first set of regressions aim to describe the characteristics of firms that invest in intangibles. We estimate the following reduced-form model:

$$investment_{jkt} = \beta_0 + \beta_1 X_{jkt-1} + \rho_{kt} + \varepsilon_{jkt} \quad (1)$$

where j denotes firm, k denotes industry and t denotes year. X_{jkt-1} is a vector of last-period firm characteristics, including FTE; self-reported competition; age; and output growth relative to the industry average. The ρ_{kt} represent a complete set of year-industry interacted fixed effects, thus allowing for each industry to have its own average investment rate and its own common time trend. In alternative specifications, we replace the industry and industry-time fixed effects with firm fixed effects (retaining only an aggregate set of year effects), thus looking at within-firm variation in the covariates and how this translates to subsequent intangible investment.

Note that our industry classification is considerably disaggregated, using level 3 ANZSIC 2006 codes which divide firms into 203 industries. Firm characteristics are lagged because of the nature of our intangible measures: as detailed in Section 3.1, firms report intangible activity over the past two years (or one year for the R&D indicator and expenditure measures), and we do not want to explain past intangible investment using current firm characteristics. We cluster standard errors at the firm level to account for within-firm correlations of the error term over time.

Table 4 presents ordinary least squares (OLS) regressions, where the intangibles measure is a firm's intangibles index in columns (1) to (3) and an indicator for the firm reporting any intangible expenditure in columns (4) to (6). In columns with age-category dummies, the omitted age category is between six and ten years old, and so all age-category coefficients are interpreted relative to this baseline. Similarly, the omitted category for self-reported competition is *many competitors, some dominant*, so competition coefficients are interpreted relative to this monopolistic-competition baseline.

Column (1) shows our baseline specification, and indicates firm size is associated with a small but statistically significant increase in the intangibles index. The coefficient of 0.057 implies that a doubling of firm size is associated with an increase of just under half an intangible investment activity for firms with no missing intangible indicators. We also see that younger firms tend to invest more; for example, the intangibles index is 0.029 greater for firms aged less than 2 relative to firms aged 6–10.

There is also evidence of some relationship between intangibles and competition, reminiscent of findings of such a relationship between innovation and competition (e.g. Aghion

et al., 2002). In particular, the estimates indicate that firms that perceive themselves to be operating in a 'captive market' engage in just under half an intangible investment less than firms with 'many competitors, some dominant.' But there is some evidence of an inverted U-shaped relationship, with intangible investment decreasing slightly for firms reporting the highest perceived competition, relative to the intermediate, baseline group.

Column (2) keeps the same controls but includes a firm's output growth four to two years ago relative to its industry average, in decimal form. This investigates whether firms that invest in intangibles are building on success or, alternatively, responding to perceived weakness in competitive performance. The coefficient estimate of 0.020 is positive and statistically significant, but is economically insignificant: a firm whose recent growth exceeded the industry average by 10 percentage points would be predicted to have an increase in the intangibles index of about .002 (0.1x.02). This indicates that intangibles-investing firms were neither thriving nor struggling prior to investment, but rather had similar momentum to other firms in their industry.

Column (3) includes firm fixed effects, to use only within-firm variation in the explanatory variables in explaining intangible investment. We control for the log of age instead of age-category dummies, because few firms make the discrete jump from one category to the other, and we would not expect large effects from crossing the thresholds.

Unsurprisingly the results become much noisier, with most estimates losing statistical significance. This means that the results in Column (1) regarding, for example, firm age, are not driven by the firms in the sample decreasing their investment as they age. Rather, the results are driven by the cross-sectional variation – a tendency for younger (or larger) sample firms to be bigger investors, all else equal, than the older (or smaller) ones. The diminished but still positive relationship between intangible investment and firm size means that in addition to the cross-sectional relationship, there is some tendency for firms' investment to increase/decrease as the grow/shrink over the sample period. Though this result is not statistically significant.

Columns (4) to (6) of Table 4 mirror the first three columns, but replace the dependent variable with an indicator for reporting any intangible expenditure. A similar picture emerges. In column (4) we see intangible investment associated positively with firm size and negatively with age, though these estimates are statistically insignificant. In terms of competition we again see a negative effect of 'captive market' and a smaller negative effect of 'many competitors, none dominant', in both cases relative to the intermediate 'many competitors, some dominant'. Column (5) shows that firms reporting any intangible expenditure experienced similar output growth to the industry average, holding all else constant; a firm whose recent growth exceeded the industry average by 10 percentage points would be expected to have an economically-tiny

0.25 percentage point higher chance of reporting any intangible expenditure ($\exp(0.1 \times 0.025) - 1$).

The firm-fixed-effects results in column (6) show point estimates that are small in magnitude and statistically insignificant. The relatively large standard errors cloud any lessons to be learnt from this specification.

Finally, we note that we have included in all of these regressions a dummy for those firms that responded “don’t know” to the competition question, and this group shows generally lower intangible investment, all else equal. We suspect this reflects such firms simply doing a poorer job overall responding to the survey, but there is no way to really know.

As further robustness explorations, Appendix Table 5 replicates Table 4 with the principal component summary of the multiple intangibles questions rather than our constructed index, and the log of reported expenditure rather than the simple yes/no indicator for expenditure. The results are qualitatively similar.

Table 4: Characteristics of intangibles-investing firms

Dependent variable:	Intangibles index (0–1)	Intangibles index (0–1)	Intangibles index (0–1)	Any intangible expenditure	Any intangible expenditure	Any intangible expenditure
Full time equivalent (ln) (2-yr lagged)	0.057*** (0.002)	0.062*** (0.003)	0.010 (0.009)	0.046*** (0.003)	0.051*** (0.004)	-0.017 (0.018)
Output growth 4-2 yrs ago relative to industry		0.020*** (0.006)			0.025** (0.010)	
Age < 2 (2-yr lagged)	0.029** (0.011)	0.032 (0.027)		0.034* (0.021)	0.086* (0.051)	
Age 2–5 (2-yr lagged)	0.011** (0.006)	0.014* (0.008)		0.005 (0.011)	-0.019 (0.015)	
Age 11–20 (2-yr lagged)	-0.011*** (0.006)	-0.011 (0.007)		-0.008 (0.009)	-0.018 (0.015)	
Age 21+ (2-yr lagged)	-0.005 (0.006)	0.003 (0.008)		-0.000 (0.010)	-0.008 (0.016)	
Log of age (2-yr lagged)			-0.004 (0.010)			0.013 (0.021)
Perceived captive market (2-yr lagged)	-0.052*** (0.011)	-0.041*** (0.014)	-0.010 (0.014)	-0.064*** (0.017)	-0.065*** (0.023)	0.004 (0.028)
1 or 2 competitors (2-yr lagged)	-0.002 (0.006)	-0.006 (0.007)	0.009 (0.007)	-0.002 (0.010)	-0.016 (0.013)	-0.015 (0.015)
Many competitors, none dominant (2-yr lagged)	-0.014*** (0.005)	-0.005 (0.007)	-0.002 (0.006)	-0.026*** (0.009)	-0.016 (0.012)	-0.010 (0.013)
Doesn't know competition (2-yr lagged)	-0.098*** (0.012)	-0.077*** (0.016)	0.029* (0.015)	-0.082*** (0.016)	-0.097*** (0.022)	0.008 (0.027)
Year * level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE			Yes			Yes
Observations	16,068	9,621	15,972	16,335	9,807	16,035
Proportion of successes				0.498	0.519	0.329
R squared	0.207	0.252	0.073	0.442	0.454	0.077

Notes: This table presents the coefficients from OLS regressions at the firm-year level where the dependent variable is an intangibles measure as described in each column header. The omitted category for age is 6–10 years, and the omitted category for competition is ‘many competitors, some dominant’. The sample is limited to March-years from 2005 to 2013. Standard errors, in parentheses, are robust and clustered at the firm level. Observation counts have been randomly rounded to base 3, for confidentiality reasons. Asterisks denote: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.2 Firm performance and past intangible investment

The next set of regressions look at firm performance outcomes after intangible investment, with versions of the following baseline model run at the firm-year level:

$$y_{jkt} = \beta_0 + \beta_1 \text{intangibles}_{jkt-1} + \beta_2 \text{age}_{jkt} + \beta_3 \text{competition}_{jkt} + \rho_{kt} + \varepsilon_{jkt} \quad (2)$$

where j denotes firm, k denotes industry and t denotes year, and y_{jkt} is a measure of firm performance, such as multi-factor productivity, labour productivity or profitability. As before, we include a complete set of industry-year interactions. We also include a ‘doesn’t-know’ intangibles index, which is constructed in the same way as our intangibles index but for the number of ‘don’t know’ answers for a firm. Hence the intangibles index is interpreted relative to the proportion of indicators not engaged in, holding constant the ‘doesn’t-know’ answers.

Strictly speaking, what should affect performance is the *stock* of intangible capital. Our intangibles indicator is more closely related to the *flow* of intangible investment than to the stock, although looking across firms the stocks and flows are typically highly correlated. If productivity depends on the stock, then the *change* in productivity from one year to the next is approximately related to the flow. Given the ambiguity of the meaning of our intangibles indicator, rather than pick a single form for this relationship, we explore a number of different variations.

Clearly the decision to invest in intangibles is endogenous; firms decide whether and when to invest. If the factors affecting that decision are correlated with the ε_{jkt} in Eq. (2), then our estimates of β_1 will be biased. While the theoretically possible ways this might occur are almost limitless, two are of particular concern in this context. First, there may be unobserved firm attributes or developments in the firm’s environment that affect both its incentive to invest in intangibles and its productivity. For example, if the firm hires a new hot-shot manager, she may increase intangible investment and she may also directly increase productivity. In that case, it will look as if intangible investment is increasing productivity even if it doesn’t. This possibility, if present, leads to an upward bias in the estimate of β_1 .

Another concern is ‘reverse causality,’ by which we mean the possibility that productivity (or profitability or another performance measure) has its own effect on intangible investment. If for, example, firms are constrained in their ability to generate the cash needed for such investment, then firms with higher productivity—which might well produce higher sales margins—would be more able to engage in intangible investment because the necessary funds are available. This would, again, lead to an upward bias in the estimate. Conversely, as mentioned above, if firms see intangible investment as a way to get themselves out of trouble, then it might be the poor-performing firms that are more likely to undertake it, which would lead to a downward bias.

In most analyses of this kind, the primary concern is that there are unobserved factors positively affecting both the investment and firm performance, leading to a concern that the effect of investment is over-estimated. As we will see, we find, if anything, negative apparent effects of intangible investment on productivity, which led us to worry more about the possibility of negative reverse causality. However, as we saw above, we find no evidence that prior firm performance is negatively associated with intangible investment, so we do not think this is driving the results. We return to consideration of these issues in the final discussion below.

4.2.1 Multifactor productivity

Table 5 presents the first set of estimates. The first 4 columns are in the form of Eq. (2), allowing the firm's MFP to vary with intangible investment, exploring sensitivity to different measures of intangible investment and different data samples. Column (1) measures intangible investment with the intangibles index, and shows a negative relationship between the level of MFP and reported intangible activity 2 years previous. (And recall that each survey asks about activity over the previous 2 years, so this is looking at the effect on MFP of intangible investment 2–4 years previous). An increase in the intangibles index corresponding to one more intangible investment out of eight is associated with a *decrease* in MFP of just under one percentage point (coefficient of about $.064 \times 1/8$). Since productivity differences among firms are typically on the order of a few percent, this is a meaningfully large effect if it is real.

Column (1) also shows the youngest firms have lower MFP, holding all else constant; firms aged 2–5 are on average 5.6 percent less productive than firms aged 6–10. The point estimates for the older age categories are negative, implying older firms are less productive, though these estimates are statistically insignificant. We also see weak evidence of an advantage for self-reported monopolists, though the estimate is also statistically insignificant. While it is possible that monopolists are truly more productive, if their measured productivity is really higher it is more likely that monopolists have higher price-cost margins, which increases revenue (deflated with an industry-based price index) and hence measured productivity (Maré, 2016).

Table 5: Firm performance and past intangible investment: multifactor productivity

Dependent variable:	MFP residual	MFP residual	MFP residual	MFP residual	2-yr change in MFP	Indicator for >5% increase in MFP
Intangibles index (2-yr lagged)	-0.064***	-0.062			0.024	0.051**
	(0.020)	(0.083)			(0.015)	(0.024)
Doesn't-know intangibles index (2-yr lagged)	-0.037	0.061			-0.009	0.008
	(0.043)	(0.166)			(0.045)	(0.051)
Any intangible expenditure (2-yr lagged)			-0.014			
			(0.011)			
Log intangible expenditure (2-yr lagged)				-0.004		
				(0.004)		
Age 2–5	-0.056***	-0.039	-0.042	-0.061**	-0.007	0.009
	(0.021)	(0.056)	(0.026)	(0.031)	(0.016)	(0.023)
Age 11–20	-0.004	0.008	-0.002	0.001	-0.013	-0.034**
	(0.012)	(0.043)	(0.014)	(0.024)	(0.010)	(0.016)
Age 21+	-0.019	0.026	-0.018	-0.028	-0.022**	-0.056***
	(0.012)	(0.048)	(0.014)	(0.022)	(0.009)	(0.016)
Perceived captive market	0.040	0.238*	0.061	0.085	0.020	0.016
	(0.044)	(0.142)	(0.053)	(0.070)	(0.020)	(0.035)
Perceived 1 or 2 competitors	0.017	0.023	0.022*	0.019	0.007	0.014
	(0.011)	(0.045)	(0.012)	(0.018)	(0.008)	(0.015)
Perceived many competitors, none dominant	-0.008	0.050	-0.007	0.006	-0.001	-0.021
	(0.011)	(0.043)	(0.012)	(0.022)	(0.009)	(0.015)
Doesn't know competition	0.011	0.013	0.028	0.028	-0.007	0.023
	(0.034)	(0.094)	(0.039)	(0.071)	(0.026)	(0.032)
Year * level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Limited to low-output sample		Yes				
Observations	7,887	885	6,078	2,325	7,029	7,029
Proportion of successes						0.316
<i>R squared</i>	0.144	0.418	0.135	0.236	0.091	0.125

Notes: This table presents the coefficients from OLS regressions at the firm-year level where the dependent variable is described in column headers. The sample is limited to odd March-years from 2005 to 2013. The low-output sample in column 3 is limited to firms in the lower quartile of output in their level 3 industry in 2004. The omitted category for age is 6–10 years, and the omitted category for competition is 'many competitors, some dominant'. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

In column (2) we limit the sample to firms who were in the lower quartile of output in their level 3 industry in 2004. The motivation is that yes/no survey questions may be less meaningful for larger firms, because a large firm is intrinsically more likely to have engaged in a given activity somewhere across the enterprise. Hence limiting the sample to small firms tests whether focusing on a context where the measures are, arguably, more meaningful shows a different picture.¹¹ We see no qualitative change in the results.

Columns (3) and (4) of Table 5 vary the measure of intangible investment employed. Column (3) is based on the dichotomous measure of whether any expenditure on intangibles is reported, and Column (4) the log of intangible expenditure for firms with positive reported expenditure. Again MFP's negative association with intangibles remains, though is not statistically significant.

As emphasized by Bontempi and Mairesse (2015), firm productivity should really be related to the *stock* of accumulated (though depreciated) intangible investment, rather than to the investment flow. This formulation is approximately equivalent to the flow being related to the *change* in firm productivity, and our intangible indicator variable is presumably most closely related to the flow because it asks about investment in the last 2 years. This approach is implemented in column (5), with a point estimate that is positive but statistically insignificant and economically modest; picking up one more intangible activity is associated with a 0.3 percentage point increase in MFP from two years ago ($0.024 \times 1/8$).

Finally, the dependent variable in column (6) is an indicator for MFP increasing by more than five percentage points. This is intended to look for the 'lottery ticket' view of intangible investment, whereby for most firms it has no effect but for a small number of (lucky?) firms it gives a big boost. The point estimate of the intangibles index is statistically significant though small in magnitude; adding one intangible investment activity is associated with with a 0.6 percentage point increase in the likelihood of having a greater than five percent increase in productivity ($0.051 \times 2/8 = 0.01275$).¹² Given that the unconditional probability of an increase of this magnitude is about 32%, this is a pretty unexciting lottery ticket, making it easy to see why the mean effect is small and statistically insignificant.

Given these hints of what looks like a possible effect of the intangible stock on productivity, we also estimated a crude stock version of the model, in which the total number of affirmative responses to the investment questions over the time period was related to end-of-period productivity levels (not reported). The sample in this specification is a balanced panel of firms appearing in the innovation modules of 2005, 2007, 2009 and 2011. We found a

¹¹ We also ran output-weighted regressions to estimate the association for the average unit of output, rather than the average firm. Results do not change qualitatively.

¹² We also ran regressions where the dependent variable is an indicator for a larger than one and a larger than 15 percentage point increase in MFP. Results are similar, with positive but economically small estimates.

systematic negative relationship between end-of-period productivity and the accumulated stock of intangibles. Finally, to further probe whether the negative association between investment and subsequent productivity levels could be due to some kind of reverse causality, we attempted to estimate a firm-fixed effects model (not reported). The results were noisy with no statistically significant coefficient estimates, and the point estimate on the lagged intangibles index was negative (-0.03)

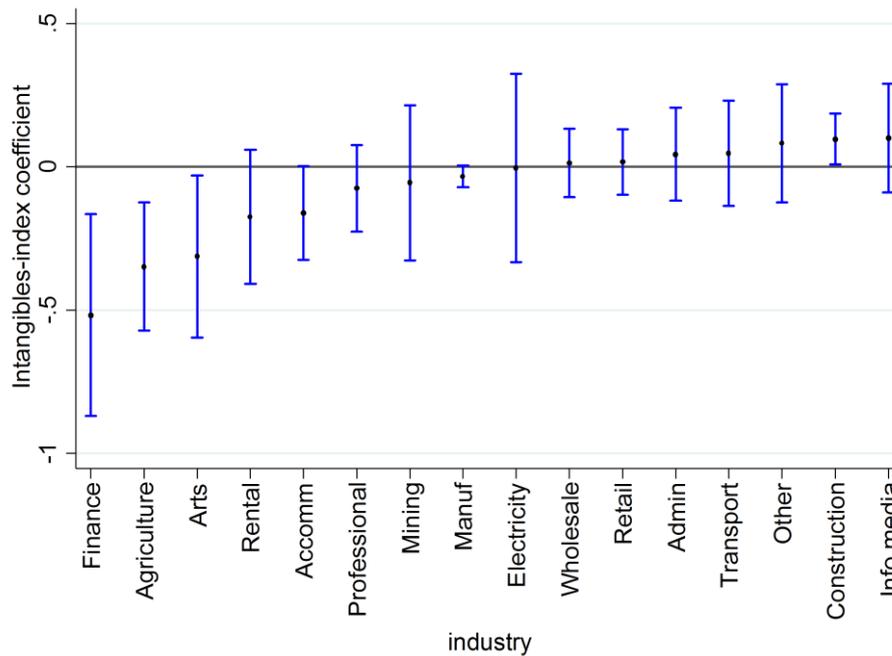
All of the results in Table 5 include age and competition variables. These are included mostly as controls, and the results for the intangible variables are not sensitive to whether or not these controls are included. For age, we find some weak evidence that younger firms (age 2–5) have lower productivity levels than the base group (age 6–10).¹³ When looking at productivity changes, we find, not surprisingly, that the oldest firms are less likely to increase their productivity. For competition, we find some evidence of higher measured productivity for firms with captive markets and only 1 or 2 competitors, consistent with market power allowing an increase in markups, which appears as higher productivity because our output measure is revenue.

Together, the results of Table 5 provide no robust evidence of a meaningful positive link between our measures of intangible investment and productivity. When modelling the level of MFP in columns (1) to (4), the point estimates are negative, and in modelling the change in MFP in columns (5) to (6), the point estimates are positive but small and statistically significant only for the ‘lottery ticket’ version. We discuss in Section 5 different possible interpretations of these results.

While our industry-year interacted effects allow the intercepts of the regression to vary flexibly, these estimates all constrain each industry to have the same coefficient on the intangibles measure. To investigate whether this is distorting the underlying relationships, Figure 4 presents separate coefficient estimates and 95 percent confidence intervals of the intangibles index for each level 1 industry, using the regression model of column (1) of Table 5. While most of the estimates are statistically insignificant (presumably due to smaller sample sizes), there is a general tendency towards negative rather than positive coefficients. Further, there is no meaningful pattern to the positives and negatives, with the negative and statistically significant coefficients appearing in two high-intangible industries (finance and arts) and one low-intangible industry (agriculture). So while this does not give us a particularly clear picture, it again calls into question any hypothesis of a positive effect of intangibles on productivity.

¹³ Note that the very youngest firms (< 2years) cannot be included in this regression because we are looking at productivity as a function of intangible investment 2 years previous.

Figure 4: Intangibles-index effect on MFP, by industry



Notes: This figure present results of specifications that replicate column (1) of **Error! Reference source not found.**, run separately by industry. Coefficients estimates and 95% confidence intervals are shown. Industries are described in Appendix Table 3.

4.2.2 Profitability and labour productivity

Table 6 similarly looks at the relationship between firm performance and past intangibles, but measures firm performance using profitability and labour productivity. In standard economic theory, firms do not care about their productivity, per se, but we assume they are trying to maximize profits. If so, then a (presumably costly) investment activity will only be undertaken if it yields a reasonable return on that investment. Since the firms' investments in intangible assets are not included in the measured capital stock of the firm, the presence of such a return on intangible assets should be reflected in higher profitability measured relative to the observed capital stock. Yet we find little evidence of a positive relationship for profitability: the coefficient estimate of the intangibles index is negative, large in magnitude and statistically significant when modelling the level of profitability in column (1); is negative though small in magnitude and statistically insignificant when modelling the change in profitability in column (3); and is positive, small in magnitude and statistically insignificant in column (5) when modelling whether a firm experienced a larger than five percent increase in profitability.

Labour productivity (value added per worker) is generally expected to rise as the result of any investment, because providing each worker with more capital should increase output per worker. Column (2) of Table 6 shows a positive relationship between intangible investment and the level of labour productivity, while column (4) shows a positive relationship between

intangible investment and the change in labour productivity. For example, the point estimate of column (4) suggests an increase in the intangibles index corresponding to one out of eight more activities is associated with about a 0.5 percentage point increase in labour productivity ($0.043 \times 1/8 = 0.0054$). Column (6) shows a positive but statistically insignificant relationship between intangible investment and the likelihood of a firm having increased labour productivity by at least five percent over the previous two years.

How do we reconcile the positive link between the intangibles index and labour productivity, when we found no such relationship for MFP or profitability? This could occur if intangible investment is associated with an increase in the amount of conventional capital per worker, whether causally or coincidentally. We will see in Section 4.4 that intangible investment is associated with large increases in revenue, capital and labour, but not with capital intensity, leaving the puzzle somewhat unresolved.

Finally, to explore a possible “growth without profitability” story and motivate the links with firm size explored in Section 4.4, Appendix Table 6 estimates versions of Eq. (2) where the dependent variable is the level, change or an indicator for meaningful change of absolute profit rather than profitability (profit per unit of capital). Absolute profit is not the best measure of performance, as it will tend to be higher for larger firms just because they are larger and have more capital. Nonetheless, firms looking to create a presence may be content with increasing absolute profits. Column (1) shows a large and statistically significant relationship between the intangibles index and the level of profits, implying taking up one out of eight more intangible activities is associated with a 19 percent increase in profits. This may reflect selection by firms, as we know larger firms tend to report more investment and will tend to have higher absolute profits. Columns (2) to (4) instead look changes in profits within a firm, and imply positive though smaller and statistically insignificant associations with the intangibles index. We explore this “growth without profitability” story in more detail in Section 4.4.

Table 6: Firm performance and past intangible investment: profitability and labour productivity

Dependent variable:	Profitability (ln) (1)	Labour productivity (ln) (2)	2-yr change in profitability (3)	2-yr change in labour productivity (4)	Indicator for >5% increase in profitability (5)	Indicator for >5% increase in labour productivity (6)
Intangibles index (2-yr lagged)	-0.312*** (0.061)	0.184*** (0.037)	-0.022 (0.051)	0.043* (0.025)	0.033 (0.028)	0.034 (0.026)
Doesn't-know intangibles index (2-yr lagged)	-0.164 (0.118)	0.018 (0.072)	-0.136 (0.119)	-0.013 (0.053)	-0.031 (0.058)	-0.004 (0.057)
Age 2-5	-0.103** (0.051)	-0.071** (0.030)	-0.001 (0.048)	-0.001 (0.025)	-0.014 (0.026)	0.026 (0.024)
Age 11-20	-0.059 (0.037)	0.035 (0.022)	0.000 (0.034)	-0.014 (0.017)	-0.012 (0.018)	-0.064*** (0.017)
Age 21+	-0.080** (0.038)	0.048** (0.022)	-0.047 (0.031)	-0.038** (0.016)	-0.049*** (0.018)	-0.100*** (0.018)
Perceived captive market	-0.074 (0.087)	0.033 (0.068)	-0.004 (0.058)	0.004 (0.029)	-0.044 (0.039)	0.017 (0.037)
Perceived 1 or 2 competitors	0.037 (0.037)	0.011 (0.021)	0.049 (0.033)	0.015 (0.014)	0.019 (0.017)	0.028* (0.017)
Perceived many competitors, none dominant	-0.056 (0.035)	-0.036* (0.019)	-0.002 (0.032)	-0.001 (0.015)	-0.034** (0.017)	0.016 (0.016)
Doesn't know competition	0.104 (0.082)	-0.138*** (0.049)	0.130* (0.071)	-0.057 (0.035)	-0.018 (0.039)	-0.051 (0.034)
Year * level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,762	7,794	5,673	6,912	5,673	6,912
Proportion of successes					0.372	0.406
<i>R squared</i>	0.267	0.365	0.161	0.156	0.161	0.156

Notes: This table presents the coefficients from OLS regressions at the firm-year level where the dependent variable is described in column headers. The sample is limited to odd March-years from 2005 to 2013. The omitted category for age is 6-10 years, and the omitted category for competition is 'many competitors, some dominant'. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

4.3 Intangibles and the distribution of firm performance

The previous section suggested that there is no positive association *on average* between intangible investment and productivity. If, however, different firms use intangible investment in different ways, it is possible that this lack of an effect on average is hiding a significant positive effect for some firms. One might think, for example, that for poorly performing firms, intangible investment is a mechanism to pull themselves up, while for successful firms it is pointless gilding of the lily. Conversely, one might think that poorly performing firms do everything badly, including making ineffective intangible investments, whereas well-run firms are able to make intangible investments that add real value. Either of these statements suggest that whether and to what extent intangible investment is productive varies depending on the underlying productivity of the firm.

Quantile regression methods allow one to explore whether the effect of a variable differs for different levels of the dependent variable. The model estimates different effects for each quantile of firm performance conditional on past intangibles and other covariates. Our model then looks like equation (2) with the same dependent and explanatory variables, but the estimator models the conditional quantile function rather than the conditional expectation function. Industry-specific time trends remain in the model for flexibility.

We also use the methodology of Firpo et al. (2009) to run *unconditional* quantile regressions that relate different parts of the unconditional distribution of firm performance to past intangible expenditure. The difference between the two methods lies in exactly which firms are in each quantile. Considering the lowest quantile, for example, the conditional method puts in that quantile the firms whose performance is worst relative to what would be expected based on their other characteristics. It would include in the lowest quantile firms whose performance is not actually so bad, if their characteristics are such that we would expect their performance to be very good. In contrast, the unconditional method includes in the lowest quantile those firms whose performance is worst in absolute terms, regardless of what we might expect based on their characteristics. In our case, we do not have a particular theory about how the effect of intangibles might vary with performance; we are simply exploring whether there is important variation underlying the average. For this reason, we try both approaches, though it turns out that they show similar qualitative pictures.

Table 7 presents results from conditional quantile regressions in odd columns, and unconditional quantile regressions in even columns.¹⁴ Columns (1) and (2) show the results for

¹⁴ In conditional quantile regressions we cluster standard errors at the firm level using the package created by Machado et al. (2015).

the intangibles index, and columns (3) and (4) use the dummy variable for reporting positive intangible expenditure. The results show that the average negative association of past intangible investment on current productivity is not limited to particular portions of the productivity distribution. There is a general pattern of negative effects, although not all are statistically significant. There is no quantile that shows a significantly positive effect for any version of the model.

The last four columns repeat this exercise but with log labour productivity as an alternative measure of firm performance. Columns (5) and (6) suggest a positive relationship between past intangibles and the various quantiles of labour productivity, with the relationship increasing as we move up the labour productivity distribution. For example, column (5) shows that increasing the past intangibles by one activity is associated with a 1.4 percent increase in the conditional 10th percentile of labour productivity ($.112 \times 1/8$), increasing to about a 1.9 percent increase in the conditional 90th percentile ($.142 \times 1/8$). Similarly, in columns (7) and (8) the coefficient estimates are consistently positive and increasing with the quantile when using an indicator for reporting any intangible expenditure.

Taken together, these results do not support the hypothesis that intangible investment behaves quite differently for firms at different points in the productivity distribution. For MFP, the association with recent past intangible investment is negative across all quantiles. For labour productivity, it is positive across all quantiles, with some evidence of a slightly larger effect for the most productive firms.

Table 7: Distribution of firm performance and past intangible investment

<i>Quantile being estimated</i>	Dependent variable: MFP				Dependent variable: log labour productivity			
	Coeff on past intangibles index	Coeff on past intangibles index	Coeff on any intangible expenditure dummy	Coeff on any intangible expenditure dummy	Coeff on past intangibles index	Coeff on past intangibles index	Coeff on any intangible expenditure dummy	Coeff on any intangible expenditure dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10th percentile	-0.012 (0.024)	-0.069*** (0.027)	-0.003 (0.013)	0.011 (0.017)	0.112** (0.051)	0.128*** (0.045)	0.059** (0.028)	0.068*** (0.025)
25th percentile	-0.037** (0.016)	-0.040*** (0.015)	-0.014* (0.008)	-0.015* (0.008)	0.139*** (0.033)	0.150*** (0.033)	0.051*** (0.019)	0.063*** (0.019)
Median	-0.035** (0.015)	-0.040*** (0.012)	-0.011 (0.008)	-0.014** (0.007)	0.124*** (0.029)	0.149*** (0.030)	0.057*** (0.016)	0.072*** (0.016)
75th percentile	-0.037* (0.019)	-0.042*** (0.016)	-0.016 (0.010)	-0.021** (0.009)	0.125*** (0.039)	0.154*** (0.037)	0.062*** (0.018)	0.088*** (0.022)
90th percentile	-0.074*** (0.025)	-0.085*** (0.032)	-0.012 (0.015)	-0.023 (0.018)	0.148*** (0.053)	0.227*** (0.058)	0.081*** (0.027)	0.104*** (0.033)
Year * level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unconditional quantile regression		Yes		Yes		Yes		Yes
<i>Observations</i>	7,884	7,884	6,075	6,075	7,794	7,794	5,997	5,997

Notes: This table presents the coefficients from quantile regressions at the firm-year level where the dependent variable is as described in column headers. Each row shows estimates of the association of past intangible investment on different part of the conditional distribution of performance (or unconditional, in every second column). Columns vary whether the distribution is conditional or unconditional, and the past intangibles measure. Regressions estimating the coefficient on the intangibles index also include as controls the 'doesn't-know' intangibles index, age-category dummies and competition dummies. The sample is limited to March-years from 2005 to 2011. Standard errors, in parentheses, are robust and clustered at the firm level in conditional quantile regressions. Observation counts have been randomly rounded to base 3, for confidentiality reasons. Asterisks denote: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.4 Changes in inputs and outputs

One explanation for the puzzling negative relationship between intangible investment and MFP in the previous sections is that firms are focused on growing; perhaps rather than increasing performance in the short-term, intangible investment is intended to bring in resources that will lead to growth, either as an end in itself or as a precondition for eventual performance gains. In this section, we investigate one of the conditions necessary for this to be true: do firms increase their inputs and outputs after investing in intangibles?

These regressions take the form:

$$y_{jkt} = \beta_0 + \beta_1 \text{intangibles}_{jkt-1} + \beta_2 \text{history}_{jkt-1} + \rho_{kt} + \varepsilon_{jkt} \quad (3)$$

where y_{jkt} denotes either the firm's log of gross output, log of labour, log of capital or log of capital intensity (capital per unit of labour); 'history' denotes the vector of past output, labour and capital, all in log form; and ρ_{kt} denotes industry-specific year effects. In alternative specifications, we drop the 'history' variable and include firm fixed effects, looking at within-firm variation in intangibles and how this translates to subsequent activity.

Table 8 presents results from such regressions, with the 'history' specifications in odd columns and the firm fixed effect specifications in even columns. The dependent variables are all in log form, so that coefficient estimates are interpreted as elasticities for the logged input and output covariates, and as semi-elasticities for the intangibles index. Column (1) shows that output tends to increase after intangible investment; an increase in the intangibles index corresponding to one additional intangible investment activity out of eight is associated with a 1.4 percent increase in output ($0.112 \times 1/8$) for a given history of past inputs and outputs. Column (2) shows an economically and statistically significant relationship remains when including firm fixed effects; an increase in the intangibles index corresponding to one additional activity out of eight is associated with a one percent increase in output ($0.079 \times 1/8$).

Columns (3) and (4) use the log of labour as the dependent variable. The results are similar; an increase of one-eighth in the intangibles index is associated with around a one percent increase for both specifications. Similarly, columns (5) and (6) use the log of capital as the dependent variable, with a coefficient on the intangibles index of .12 when controlling for a firm's history of inputs and outputs, and .08 with firm fixed effects.

As noted above, the positive association of intangible investment with labour productivity when it is not positively associated with MFP suggests that perhaps intangible investment is associated with an increase in conventional capital intensity. The results in columns (3) – (6) do not show an obvious tendency in terms of the relative increase in capital and labour. The last two columns of Table 8 look directly at the log of capital intensity, measured as capital per unit

of labour. The positive point estimate of 0.028 in column (7) is economically small and statistically insignificant, and the negative point estimate of -0.036 in column (8) with firm fixed effects is similarly economically small and statistically insignificant.

Together, the results of Table 8 provide strong evidence that increases in the intangibles index are associated with increases in firm inputs and outputs; firms expand after intangible investment. But capital intensity appears unchanged; there is no clear difference between the growth of capital and labour inputs. This leaves unresolved the puzzle of the positive associations with labour productivity shown in previous sections; intangibles-investing firms are using more labour and capital after investment, in roughly the same proportion, and it looks like they subsequently have higher labour productivity but not MFP.

Table 8: Intangible investment and growth of inputs and output

Dependent variable:	Gross output (ln) (1)	Gross output (ln) (2)	Labour (ln) (3)	Labour (ln) (4)	Capital (ln) (5)	Capital (ln) (6)	Capital intensity (ln) (7)	Capital intensity (ln) (8)
Intangibles index (2-yr lagged)	0.112*** (0.024)	0.079** (0.033)	0.092*** (0.021)	0.113*** (0.030)	0.120*** (0.024)	0.077** (0.036)	0.028 (0.023)	-0.036 (0.034)
Doesn't-know intangibles index (2-yr lagged)	-0.038 (0.059)	0.044 (0.048)	-0.003 (0.042)	0.054 (0.043)	-0.012 (0.070)	0.050 (0.055)	-0.008 (0.057)	-0.005 (0.052)
Gross output (ln) (2-yr lagged)	0.889*** (0.018)		0.065*** (0.012)		0.106*** (0.015)		0.040*** (0.015)	
Labour (ln) (2-yr lagged)	0.080*** (0.016)		0.929*** (0.013)		0.031** (0.016)		0.860*** (0.012)	
Capital (ln) (2-yr lagged)	0.034*** (0.009)		-0.002 (0.007)		0.858*** (0.013)		-0.898*** (0.016)	
Year * level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes		Yes
Observations	9,285	10,485	9,285	10,485	9,285	10,485	9,285	10,485
Number of firms		6,273		6,273		6,273		6,273
R squared	0.919	0.114	0.903	0.118	0.924	0.096	0.820	0.080

Notes: This table presents the coefficients from OLS regressions at the firm-year level where the dependent variable is as described in column headers, in natural log form. Capital intensity is measured as capital per unit of labour. The sample is limited to odd March-years from 2005 to 2013. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

4.5 Reported satisfaction and intangible investment

The results so far suggest that intangible investment is associated with growth, but with no positive effect on firms' productivity or profitability. This led us to explore further what might be happening when firms invest in intangibles that foster growth while not increasing profits or productivity. One possibility is that intangibles support improvement in 'soft' aspects of firm performance that are not reflected in the short run in productivity or profitability. As an exploration of this possibility, we examine whether past intangible investment is associated with higher firm-reported customer and employee satisfaction for firms that look otherwise similar. Our baseline model is a linear probability model and takes the form:

$$y_{jkt} = \beta_0 + \beta_1 \text{intangibles}_{jkt-1} + \beta_2 \text{confidence}_{jkt-1} + \gamma_k + \delta_t + \varepsilon_{jkt} \quad (4)$$

where j denotes firm, k denotes industry and t denotes year, and y_{jkt} is an indicator for the firm reporting soft success (either high customer or high employee satisfaction). We derive this indicator of success from a question asking whether a business is lower, on par with or higher than competitors when it comes to customer and employee satisfaction (as described in Section 3.1); the dependent variable takes on the value one if the firm reports high customer/employee satisfaction, and zero otherwise, ignoring 'don't know' answers. The 'confidence' variable is described in Section 3.1 and controls for the fact that some managers may generically overstate how great their firm is. We also include industry-specific year effects to allow each industry to have its own time trend of reported satisfaction. Hence we examine whether past intangible investment is associated with more customer and employee satisfaction for comparable firms reporting similar levels of quality; flexibility; time to produce goods and services; and costs.

Table 9 presents results of this estimation. Column (1) shows a positive and statistically significant relationship between the lagged intangibles index and firm-reported customer satisfaction. The coefficient estimate of 0.092 indicates that adding one additional intangible activity is associated with 1.1 percentage point increase ($0.092 \times 1/8$) in the probability of reporting high customer satisfaction.

One concern with such a specification is that certain managers may be overly confident about their firm's quality, causing them to overstate the satisfaction of their customers and employees. Furthermore, these same respondent-specific traits may correspond with reporting intangible investment; overly confident managers may like to report that they are training their employees, developing new marketing strategies and doing other admirable-sounding activities. If this omitted-variable hypothesis is correct, our coefficient estimate of the intangibles index will be upwardly biased in column (1). We attempt to control for the 'confidence' of the survey respondent using the confidence index as a control, as described in Section 3.1 and constructed

as the average reported category for questions on relative costs; relative time to provide goods and services; relative quality of goods and services; and relative flexibility.

Column (2) of Table 9 shows that including the confidence index as a control decreases but leaves positive the point estimate of the intangibles index. As expected, the coefficient estimate on the confidence index is positive, indicating that firms answering higher on the underlying questions tend to report more intangible investment. Column (3) instead controls for respondent confidence by including dummy variables for each of the categories that make up the confidence index. The coefficient estimate of the intangibles index loses statistical significance though remains positive.

Columns (4) to (6) replicate columns (1) to (3) but with employee satisfaction as the dependent variable. A similar pattern emerges; intangible investment is positively associated with employee satisfaction, with the relationship becoming weaker but remaining positive and statistically significant after attempting to control for the confidence of the firm. For example, column (5) indicates that adding one of the eight intangible activities is associated with a 0.75 percentage point increase ($0.06 \times 1/8$) in the likelihood of reporting high employee satisfaction. Appendix Table 7 replicates Table 9, but estimates logit models rather than linear probability models.¹⁵ Because the coefficient estimates from a logit model are not directly interpretable, the comparison to the results of Table 9 are slightly tricky, but with appropriate calculation of the average marginal effects the results are very close to the corresponding point estimates from Table 9.

We have not established causality with these estimates; intangible investment may be correlated with the error term in these models due to omitted variable bias. There could be separate phenomena pushing up both intangible investment and customer/employee satisfaction or reverse causality between satisfaction and intangible investment that cannot be solved by lagging our intangibles index. However, it is interesting that the finding holds after comparing similar firms within an industry, and controlling for how confident the firm is on other dimensions. This suggests a channel through which intangible investment may be affecting firms' outcomes.

¹⁵ We drop industry-specific year effects for empirical tractability, but leave in both year and industry fixed effects

Table 9: Intangible Investment and Customer/Employee Satisfaction

Dependent variable:	High customer satisfaction	High customer satisfaction	High customer satisfaction	High employee satisfaction	High employee satisfaction	High employee satisfaction
	(1)	(2)	(3)	(4)	(5)	(6)
Intangibles index (2-yr lagged)	0.092*** (0.021)	0.055*** (0.019)	0.008 (0.016)	0.085*** (0.022)	0.060*** (0.021)	0.034* (0.020)
Doesn't-know intangibles index (2-yr lagged)	-0.133*** (0.047)	-0.128*** (0.041)	-0.098*** (0.219)	-0.110** (0.047)	-0.105** (0.044)	-0.083* (0.043)
Arrogance index (1-3)		0.593*** (0.012)			0.418*** (0.014)	
Dummies for reported costs, time to provide g&s, quality and flexibility			Yes			Yes
Year * level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Proportion of successes	0.628	0.628	0.627	0.493	0.493	0.493
<i>Observations</i>	13,293	13,269	13,173	12,636	12,603	12,522

Notes: This table presents the coefficients from OLS regressions at the firm-year level where the dependent variable is a dummy variable for the firm reporting an aspect of soft success, as described in column headers. The sample is limited to March-years from 2005 to 2013. Standard errors, in parentheses, are robust and clustered at the firm level. Observation counts have been randomly rounded to base 3, for confidentiality reasons. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

5 Conclusion

A growing literature on intangible investment posits—and sometimes confirms empirically—that such investment results in an intangible asset of the firm that improves firm performance. In the standard the model, the presence of this productive input that is not included among measured inputs should be reflected in higher productivity and profitability as conventionally measured.

Using firm-level data from the LBD, we link self-reported intangible investment activities including R&D, employee training, marketing and organisational restructuring with measures of firm performance and activity. We find evidence of plausible variation in our intangible measures across different industries: our measure of intangible investment is highest in ‘information media and telecommunications’; ‘manufacturing’; and ‘professional, scientific and technical services’. It is lowest in ‘agricultural, forestry and fishing’; and ‘mining’.

Looking at the characteristics of intangibles-investing firms, we find that intangible investment is decreasing with age; increasing with firm size; is unrelated to past output growth relative to the industry average; and is highest with a moderate amount of perceived competition.

Intangible investment in the recent past appears negatively associated with MFP, though we do find a small, statistically significant positive effect of recent past intangible investment on the probability of enjoying a large productivity increase. When we look at intangibles and the distribution of MFP, we find a generally negative relationship across different quantiles, though it is most negative for the highest quantiles.

More generally, we have tried many different empirical formulations of the relationship and have found no framework in which strong positive effects of such investment on productivity or profitability can be detected.¹⁶ Typically, we would expect the associations shown to be *upwardly* biased due to unobserved attributes of good management being positively correlated with both intangible investment and productivity. This makes the negative relationship all the more puzzling. While there is a theoretical possibility of negative bias due to causality running from low productivity to intangible investment, this seems unlikely given that intangible investment seems unrelated to a firm’s past output growth relative to the industry average.

Although we have not estimated a causal model, the data show an association between firm growth and intangible investment, and seem to be consistent with a story in which such

¹⁶ In addition to the models reported herein, we also explored whether any individual forms of intangible investment or categories of such investment as used by Corrado, et al (2012) have positive associations with productivity. We found none.

investment allows the firm to attract additional inputs and increase its revenue. We have not pinned down the mechanisms by which this might work, but we do find that past investment is positively correlated with firm-reported customer and employee satisfaction. This finding holds after attempting to control for the possible tendency of some firms to overstate their accomplishments.

Given the weakness of the results, and their apparent inconsistency with theory, it is hard to draw strong conclusions from this analysis. The results may be driven by some combination of:

1. The BOS survey responses do not meaningfully reflect 'true' intangible investment.
2. Our LBD-derived productivity and profitability measures do not accurately capture true productivity and profitability.
3. Intangible investment can increase productivity, but on average New Zealand firms are investing in the wrong assets, or are investing inefficiently.
4. Intangible investment does improve firm performance, but this effect is clouded by some kind of reverse causality or negative selection into intangible investment.
5. Intangible investment does improve firm performance, but with long and/or variable lags that make it impossible to identify empirically.
6. Firms invest in intangibles in pursuit of firm growth, even if such growth occurs at the expense of productivity and/or profitability.
7. Firms may invest in intangibles for benefits that are themselves intangible, such as customer and employee satisfaction.
8. Firms may investment in intangibles expecting that it will allow them to grow and become more profitable/productive, but the latter outcomes are mostly unrealized.

Explanation 1 has some plausibility; self-reported answers to broad questions will never perfectly capture the phenomenon of interest. But given the systematic relationships in our regression analysis and the variation across industries, it seems we are measuring real-world intangible investment to some extent, and it is difficult to imagine a systematic pattern of mismeasurement that would produce apparent negative effects. Similarly, mismeasurement of profitability and productivity would seem more likely to yield no effect than a negative effect. Explanation 3 is more a caveat on interpreting our results. Any analysis of this kind can say only what is, not what could be. But we did look to see whether *any* of the avenues of intangible investment in the data could be seen to have positive effects, and found none. And the measures we do have are associated with measurable differences for firms—they grow faster. We cannot rule out that they could have had other effects if undertaken differently, but we are more inclined to focus on what did happen.

Explanation 4 seems implausible to us; strong negative selection on MFP into intangibles would suggest something closer to a survival story in which firms invest in a last-ditch effort remain afloat. But our results show investing firms tend to have had growth similar to the industry average, which is not consistent with a widespread survival-motive.

Explanation 5 has surface plausibility. Intangible investment is associated with increased costs in the short run and so could manifest as a negative effect in the short run while eventually bearing fruit. We are personally sceptical of this explanation. Our main results measure intangible investment 2–4 years previous, and it seems unlikely that lags longer than that could yield overall positive investment results. Further, even when we cumulate investment over our entire period, we find a negative association with end-of-period productivity.

“Explanations” 6 - 8 are consistent with the data, but they are not really explanations in any fundamental sense. They suggest questions about how firms see their strategic choices, and why they choose the options they do. But they are healthy reminders that firms are complex institutions operating under their own objectives and constraints. Researchers’ focus on productivity and profitability may not correspond even conceptually to the goals that firms and their owners pursue. And what firms seek and what they achieve may not necessarily be the same.

Because of these uncertainties, the policy implications of these findings seem limited. On one level, it is useful simply to remind ourselves that even with mounds of data we have only a pretty cloudy lens through which to view firm behaviour. We can and should continue to try to understand better what is going on, but we should have no illusions that with enough data and the right econometrics we can produce The Answer.

These results do suggest that if productivity improvement is the goal, encouraging investment in the activities we have considered is unlikely to be a powerful tool, at least without better understanding how intangible investment translates (or fails to translate) into intangible assets. This is a topic for further research, though there are inherent measurement difficulties.

If firms themselves are truly more focused on growth than on profitability, policy prescriptions become quite tricky. The standard formulation of seeking public policies that rectify market failures is predicated on the basic welfare economics optimality results, which in turn rest on the assumption of profit-maximizing behaviour. A model in which firms systematically seek growth rather than profits may well be realistic, but it requires a rethinking of the appropriate role for government.

Finally, if firms systematically seek profits but systematically fail to use intangible investment effectively toward that end, then there are clearly some informational issues to be dealt with. Figuring out if policy could improve on this situation will require a better understanding of how and why firms make the decisions they do.

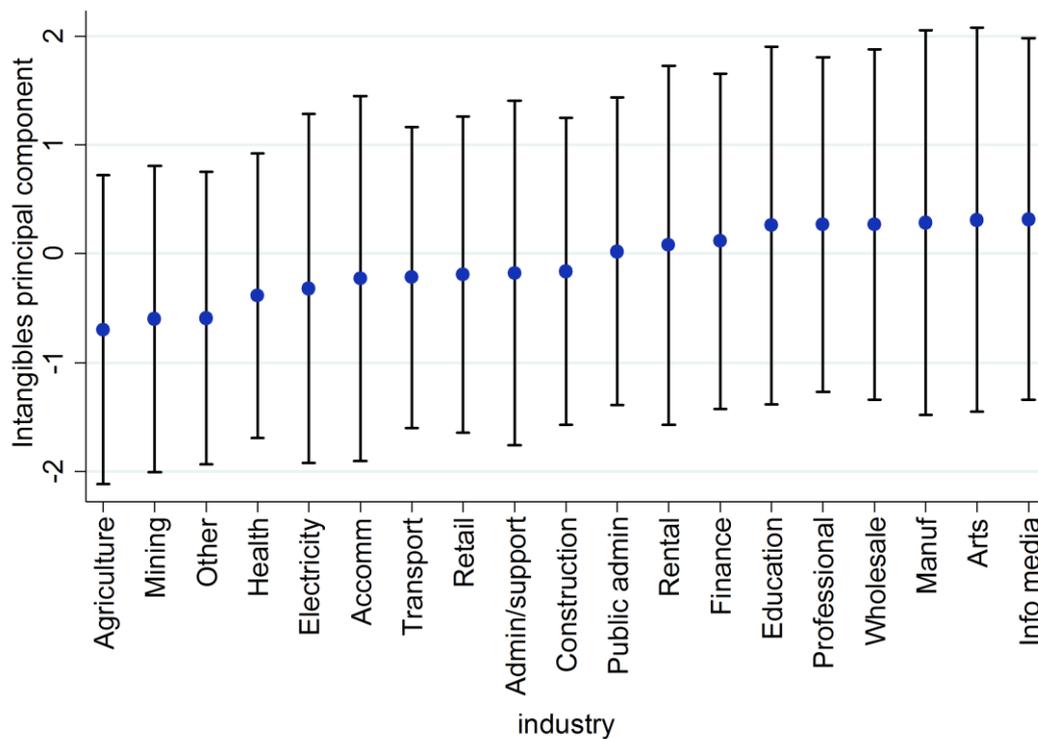
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Appendix

Appendix Figure 1: Mean and spread of intangibles principal component, by industry



Notes: Appendix Figure 1 presents, as blue dots, the mean intangibles principal component for all firm-years by industry over the period 2005–2013. The black bands show all values falling within one standard deviation of the mean for each industry. Full industry descriptions are given in Appendix Table 3.

Appendix Table 1: Correlation matrix of intangible indicators

	Com-puter-ware	New business strategies	Organis. restructuring	Desi-gn	Market research	Chang-es to mkting	Empl-oyee training
New business strategies	0.416						
Organis. restructuring	0.345	0.691					
Design	0.316	0.381	0.328				
Market research	0.327	0.474	0.389	0.445			
Changes to mkting	0.287	0.623	0.479	0.451	0.616		
Employee training	0.510	0.438	0.388	0.194	0.393	0.318	
R&D	0.223	0.292	0.265	0.464	0.432	0.282	0.186

Notes: Tetrachoric correlations are derived from the cross-section of all innovation BOS modules, 2005–2013. Descriptions are abbreviated. See Section 3.1 for full descriptions.

Appendix Table 2: Principal components of intangibles indicators

	1st component weights	2nd component weights
Acquisition of computer hardware & software	0.312	-0.372
Implementing new business strategies/management techniques	0.416	-0.181
Organisational restructuring	0.373	-0.207
Design	0.330	0.452
Market research	0.387	0.209
Significant changes to marketing strategies	0.393	0.108
Employee training	0.315	-0.489
Research and development	0.280	0.536

Notes: The two components with eigenvalues larger than 1 are shown. Principal components are derived from the tetrachoric correlation matrix shown in **Error! Reference source not found.**

Appendix Table 3: ANZSIC 2006 industry codes

Code	Industry description	Abbreviation
A	Agriculture, Forestry and Fishing	Agriculture
B	Mining	Mining
C	Manufacturing	Manuf
D	Electricity, Gas, Water and Waste Services	Electricity
E	Construction	Construction
F	Wholesale Trade	Wholesale
G	Retail Trade	Retail
H	Accommodation and Food Services	Accomm
I	Transport, Postal and Warehousing	Transport
J	Information Media and Telecommunications	Info media
K	Financial and Insurance Services	Finance
L	Rental, Hiring and Real Estate Services	Rental
M	Professional, Scientific and Technical Services	Professional
N	Administrative and Support Services	Admin/support
O	Public Administration and Safety	Public admin
P	Education and Training	Education
Q	Health Care and Social Assistance	Health
R	Arts and Recreation Services	Arts
S	Other Services	Other

Notes: Codes and industry descriptions come from Statistics NZ. Abbreviations are the authors' own.

Appendix Table 4: Intangibles by industry, controlling for firm size

Variable	intangibles index
Full-time equivalent (ln) (2-yr lagged)	0.044*** (0.001)
Agriculture	-0.064*** (0.010)
Mining	-0.052*** (0.017)
Manuf	0.058*** (0.009)
Electricity	0.008 (0.017)
Construction	-0.016 (0.011)
Wholesale	0.049*** (0.011)
Retail	-0.041*** (0.011)
Accomm	-0.021* (0.013)
Transport	-0.047*** (0.011)
Info media	0.081*** (0.013)
Finance	0.051*** (0.011)
Rental	0.042*** (0.013)
Professional	0.057*** (0.010)
Admin/support (omitted)	- -
Public admin	0.008 (0.037)
Education	0.079*** (0.016)
Health	-0.044*** (0.011)
Arts	0.067*** (0.019)
Other	-0.029** (0.014)
<i>Observations</i>	29,547
<i>R-squared</i>	0.090

Notes: This table regresses a firm's intangibles index on previous firm size and industry dummies. Full industry descriptions are given in Appendix Table 1. The observation count has been randomly rounded to base 3, for confidentiality reasons.

Appendix Table 5: Characteristics of intangibles-investing firms, robustness check

Dependent variable:	Intangibles principal component	Intangibles principal component	Intangibles principal component	Intangible expenditure (ln)	Intangible expenditure (ln)	Intangible expenditure (ln)
Full time equivalent (ln) (2-yr lagged)	0.375*** (0.014)	0.408*** (0.017)	0.082 (0.060)	0.409*** (0.017)	0.439*** (0.020)	0.221* (0.126)
Output growth 4-2 yrs ago relative to industry		0.130*** (0.039)			0.019 (0.056)	
Age < 2 (2-yr lagged)	0.197*** (0.076)	0.194 (0.178)		0.059 (0.126)	-0.516 (0.400)	
Age 2-5 (2-yr lagged)	0.071* (0.039)	0.097* (0.054)		-0.011 (0.055)	-0.117 (0.076)	
Age 11-20 (2-yr lagged)	-0.073** (0.037)	-0.065 (0.048)		0.030 (0.046)	0.002 (0.062)	
Age 21+ (2-yr lagged)	-0.042 (0.042)	0.027 (0.053)		-0.025 (0.050)	-0.086 (0.065)	
Log of age (2-yr lagged)			-0.001 (0.069)			0.261 (0.200)
Perceived captive market (2-yr lagged)	-0.340*** (0.072)	-0.270*** (0.094)	-0.083 (0.098)	0.028 (0.103)	0.085 (0.165)	-0.217 (0.248)
1 or 2 competitors (2-yr lagged)	-0.002 (0.037)	-0.041 (0.048)	0.076 (0.049)	0.050 (0.045)	0.071 (0.062)	-0.244** (0.119)
Many competitors, none dominant (2-yr lagged)	-0.087** (0.034)	-0.033 (0.045)	-0.008 (0.040)	0.010 (0.042)	0.018 (0.054)	-0.001 (0.087)
Doesn't know competition (2-yr lagged)	-0.616*** (0.082)	-0.454*** (0.106)	0.183* (0.103)	0.090 (0.084)	0.114 (0.129)	-0.135 (0.306)
Year * level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE			Yes			Yes
Observations	15,615	9,363	15,519	8,136	5,094	5,271
R squared	0.213	0.260	0.079	0.950	0.952	0.215

Notes: This table presents the coefficients from OLS regressions at the firm-year level where the dependent variable is an intangibles measure as described in each column header. The sample is limited to March-years from 2005 to 2013. In columns (4) to (6) the sample is limited to firms with positive reported intangible investment. The omitted category for age is 6-10 years, and the omitted category for competition is 'many competitors, some dominant'. Standard errors, in parentheses, are robust and clustered at the firm level. Observation counts have been randomly rounded to base 3, for confidentiality reasons. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

Appendix Table 6: Absolute profits and past intangible investment

Dependent variable:	Absolute profit (ln)	2-yr log difference in absolute profit	Indicator for >5% increase in abs. profit	Indicator for >25% increase in abs. profit
	(1)	(2)	(3)	(4)
Intangibles index (2-yr lagged)	1.480*** (0.097)	0.053 (0.050)	0.033 (0.028)	0.034 (0.026)
Doesn't-know intang. index (2-yr lagged)	0.561*** (0.207)	-0.090 (0.102)	-0.031 (0.058)	-0.004 (0.057)
Age 2–5	-0.226*** (0.079)	0.062 (0.048)	-0.014 (0.026)	0.026 (0.024)
Age 11–20	0.264*** (0.060)	-0.041 (0.032)	-0.012 (0.018)	-0.064*** (0.017)
Age 21+	0.595*** (0.065)	-0.079*** (0.031)	-0.049*** (0.018)	-0.100*** (0.018)
Perceived captive market	-0.200 (0.141)	-0.031 (0.057)	-0.044 (0.039)	0.017 (0.037)
Perceived 1 or 2 competitors	-0.158** (0.063)	0.055* (0.032)	0.019 (0.017)	0.028* (0.017)
Perceived many competitors, none dominant	-0.210*** (0.055)	0.010 (0.032)	-0.034** (0.017)	0.016 (0.016)
Doesn't know competition	-0.386*** (0.124)	0.085 (0.066)	-0.018 (0.039)	-0.051 (0.034)
Year * level 3 industry FE	Yes	Yes	Yes	Yes
<i>Observations</i>	6,762	5,673	5,673	6,912
<i>Proportion of successes</i>			0.372	0.406
<i>R squared</i>	0.377	0.160	0.161	0.156

Notes: This table presents the coefficients from OLS regressions at the firm-year level where the dependent variable is described in column headers. The omitted category for age is '6–10 years' and the omitted category for competition is 'many competitors, some dominant'. The sample is limited to odd March-years from 2005 to 2013. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

Appendix Table 7: Intangible investment and customer/employee satisfaction, logit regression

Dependent variable:	High customer satisfaction (1)	High customer satisfaction (2)	High customer satisfaction (3)	High employee satisfaction (4)	High employee satisfaction (5)	High employee satisfaction (6)
Intangibles index (2-yr lagged)	0.405*** (0.090)	0.254*** (0.098)	0.048 (0.109)	0.351*** (0.089)	0.265*** (0.092)	0.179* (0.095)
Doesn't-know intangibles index (2-yr lagged)	-0.532*** (0.194)	-0.626*** (0.209)	-0.575** (0.225)	-0.476** (0.198)	-0.498** (0.206)	-0.440** (0.215)
Confidence index (1-3)		3.131*** (0.083)			1.882*** (0.070)	
Dummies for reported costs, time to provide g&s, quality and flexibility			Yes			Yes
Year & level 3 industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Proportion of successes	0.628	0.628	0.627	0.494	0.493	0.493
Observations	13,248	13,224	13,128	12,597	12,564	12,480
Avg marginal effects of intangibles index (discrete change 0→1)						
Pr (dep var = higher than competitors)	0.091*** (0.020)	0.047*** (0.018)	0.007 (0.016)	0.084*** (0.021)	0.058*** (0.020)	0.036* (0.019)

Notes: This table presents the coefficients from logit regressions at the firm-year level where the dependent variable is a dummy variable for the firm reporting an aspect of soft success, as described in column headers. The sample is limited to March-years from 2005 to 2013. Standard errors, in parentheses, are robust and clustered at the firm level. Observation counts have been randomly rounded to base 3, for confidentiality reasons. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

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