Competition and productivity: Do commonly used metrics suggest a relationship?

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The results in this paper are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Stats NZ. The opinions, findings, recommendations, and conclusions expressed in this paper are those of the author(s), not Stats NZ, other Productivity Hub agencies, the Commerce Commission or Motu. Access to the anonymised data used in this study was provided by Stats NZ under the security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this paper have been confidentialised to protect these groups from identification and to keep their data safe. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz. The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes. Any person who has had access to the unit record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

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Abstract

We demonstrate the power of recently redeveloped productivity microdata to produce a range of meaningful competition indicators highlighting different aspects of industry competitiveness. Combining these competition metrics into composite indicators, we summarise the diverse range of competitive environments in New Zealand by clustering industries into four distinct groups. Estimating the relationship between competition and productivity within these groups provides some suggestive results that the tail of unproductive firms may be truncated when competition is greater, in part due to greater selection-to-exit based on productivity. Overall, the limited evidence we find for a direct relationship between competition and productivity does not necessarily imply that the two are unrelated, but more likely reflects that changes in competition in New Zealand over the sample period have not been particularly pronounced, making it difficult to identify a systematic relationship.

JEL codes

D22; D24; L11

Keywords

competition; profit elasticity; price-cost margin; industry concentration; multifactor productivity

Summary haiku

More competition
to lift productivity
(Where) can we see that?

1 Motivation

We expect competitive markets to facilitate aggregate productivity growth through several mechanisms, including the reallocation of resources to more productive firms, and by encouraging firms to make productivity-enhancing investments (Syverson 2011).[1] While at some point additional competition may exert a brake on innovation by restricting (desirable) returns to investment (Aghion et al. 2005), policymakers are justified to feel concerned about understanding the competitive nature of markets, particularly in countries such as New Zealand, where domestically-focussed product markets may be thin due to the small size of the economy.

To improve understanding of competition in New Zealand, this paper makes two distinct contributions. Firstly, we exploit the recent creation of better and more up-to-date firm-level productivity and profit data (Fabling and Maré 2019) to update and revise the existing suite of competition metrics produced by the Ministry of Business, Innovation and Employment (MBIE 2016; Gardiner 2017).[2] Data quality improvements are important to measurement on at least two dimensions: we use newly-available weights to reflect the underlying population of firms, likely improving estimates of aggregates such as industry concentration measures; and the preferred MBIE competition metric (MBIE 2016) relies on econometric estimation, which is biased towards zero (low competition) in the presence of measurement error. Such a bias is problematic for understanding trends in competition if the degree of error in the data varies over time, and is problematic for cross-country comparison if data quality varies across countries (even in the presence of near-identical empirical specifications, as in MBIE 2016).

Beyond data quality improvements, we derive composite indicators of competition, which combine the signal in the many alternative competition measures using principal component analysis. Since each measure potentially identifies different aspects of competition (or a lack thereof), combining common components and interpreting them collectively may represent a superior approach to picking a single "preferred" metric. Additionally, examining the correlation between metrics aids our understanding of what each measure captures, particularly in situations where a metric may differ empirically

[1] This expectation does not assume that productivity dispersion is synonymous with resource misallocation since productivity-enhancing experimentation can lead to increasing dispersion (Brown et al. 2016; Haltiwanger et al. 2018).

[2] MBIE (2016) summarises a large body of prior unpublished (not for citation) work by MBIE and Ministry of Economic Development staff.

from its optimal theoretical construct. In our analysis, as with others before us (Boone 2008; Griffith et al. 2005), key compromises relate to the use of average rather than marginal costs, and relying on the industry classification to identify markets.

Our second contribution is an exploration of the link between competition measures and productivity outcomes. Specifically, we test whether increasing (measured) competition is related to increasing turnover (entry/exit) of businesses in an industry, whether that turnover contributes to aggregate multifactor productivity (MFP) growth through a selection effect, and whether competition affects the degree of dispersion between high and low productivity firms in an industry, perhaps driven by entry/exit dynamics or through other mechanisms.

To motivate this analysis, we begin with simple regressions relating long-run changes in productivity growth/dispersion to long-run changes in competition, as measured by each of the individual metrics. The bulk of the subsequent analysis then focuses on the principal components, and their relationship with industry productivity growth. A key strength of this analysis is the flexibility of the labour and productivity datasets on the Longitudinal Business Database to be able to produce internally consistent measures of MFP, total variable costs and labour compensation.

Section 2 briefly summarises the expected relationship between competition and productivity, while section 3 discusses the data, describing the competition and productivity metrics used. Section 4 outlines the empirical approach to estimating the relationship between competition and productivity, with results of that analysis reported in section 5. Section 6 briefly summarises the findings and discusses avenues for further research.

2 The competition-productivity relationship

The importance of competition policy as a tool for raising productivity and productivity growth stems from the negative outcomes that can arise when firms are able to exercise market power. When firms face strong competition, they are unable to set prices above their marginal variable cost. If they do, competing firms can enter the market and sell at a lower price without making a loss. In simple economic models, firms charging above the competitive price would lose all of their customers. When firms do not face such competition, they have the market power to raise prices, albeit generally with the loss of some customers. Selling a reduced quantity of output at a higher price has two effects: first, it reallocates economic welfare from customers to suppliers, and second, it reduces the total economic welfare that can be generated from the available set of inputs – a "deadweight loss" that is at the heart of economists' enthusiasm for competitive markets.

Productivity measures capture the amount of output that is produced with inputs. Clearly, the reduced output resulting from market power generates a positive expected relationship between competition and productivity. The negative impact of market power on productivity is, however, broader than this. Previous research has identified both static and dynamic mechanisms by which market power can, and does, reduce the level or growth of productivity.[3]

Competition acts as a discipline on firms, forcing them to keep costs and prices down for fear of losing customers to competing firms. As Adam Smith noted in the context of agricultural production, "monopoly... is a great enemy to good management" (Smith 1776). Bloom and Van Reenen (2010) document the prevalence of better management practices in industries where competition is stronger.

More generally, when technologies, products and demand change over time – as is the case in most markets – market power can have a more substantial effects on the level and growth of productivity. In the absence of competition, firms have less incentive to innovate or invest in risky changes that could improve their productivity. At the industry level, market power can impede productivity growth by affecting the entry and survival of more productive or innovative firms.

For example, Syverson (2004) examines local market power in the US concrete industry. Because concrete must be used close to where it is produced, market power varies depending on the size of local markets. In addition, the output is fairly homogeneous and measurable, making the industry attractive for empirical research. Syverson finds that concrete suppliers in more competitive markets are more productive, and that this difference is strongly related to the ability of less productive firms to remain in business in less competitive locations. The ability of new relatively productive firms to enter the market, and inability of less productive firms to survive is a key mechanism by which productivity in an industry can be maintained or increased. This mechanism can also reallocate resources from less productive to more productive industries.

[3] See Syverson (2011), CMA (2015) or Holmes and Schmitz (2010) for reviews of evidence.

In examining the relationship between competition and firm or industry performance, we consider a variety of competition measures, and a variety of performance measures. We do this because no one competition or performance measure is fully informative about the links between competition and performance. The abstract theoretical model of "perfect" competition is useful for understanding the operation of markets in the absence of market power. Market power can, however, take many forms. It can also arise from a variety of sources, including economies of scale, control of scarce resources, innovation, or regulatory barriers to entry, exit and knowledge transfer. In some but not all cases firms can actively reinforce and strengthen their market power by predatory pricing or other anti-competitive behaviours. Preventing such behaviour is a key focus of competition regulation.

Different competition indicators reflect different departures from perfect competition. As outlined below, we consider competition indicators that reflect the presence of firms with a disproportionately large share of industry employment or output (Herfindahl and dominance measures), as well as measures that reflect price-setting behaviour (price-cost margins and profit elasticity). It is possible that an industry appears competitive on some measures and uncompetitive on others. For instance, localised retail industries may lack dominant players nationally but still have high price cost margins because of market power locally. Similarly, if an industry contains heterogeneous firms supplying differentiated products (eg, professional services), average markups may be sustained even in the absence of dominant firms. Alternatively, import competition may keep margins low even where there a market is dominated by a few large players within New Zealand.

In order to summarise the range of distinct patterns of competition measures across industries, we construct three *composite indicators,* using the method of principal components. We then group industries based on whether they are high or low on each of the composite indicators, yielding five industry groupings.

3 Data, competition & productivity metrics

3.1 Data

To construct the necessary competition metrics, we need firm-level data on output (Y), intermediate consumption (M), labour costs (W) and total labour input (L). These data come from the labour and productivity datasets (Fabling and Maré 2015a, 2015b, 2019) in the Longitudinal Business Database (LBD), which have recently been updated to include sixteen financial years (2001-2016).

Labour data originate from monthly pay-as-you-earn (PAYE) and annual tax data in the Integrated Data Infrastructure (IDI), which are cleaned and transformed using the methodology outlined in Fabling and Maré (2015a). The unit of observation is the permanent enterprise, which improves the longitudinal continuity of enterprise identifiers using employee tracking (Fabling 2011). While enterprise group may be a more appropriate unit of analysis for competition studies, data issues prevent the implementation of a group-level approach using financial data.[4]

During the most recent data update, several enhancements were introduced to the productivity data that aid our analysis, notably testing to ensure that productivity and labour data are internally consistent in their measurement of W, and the addition of population weights to account for missing data (Fabling and Maré 2019). The consistent measurement of labour costs across data sources means we can confidently combine the productivity and wage data to get profit-like measures. We use the population weights – based on annual industry-firm-size cells – throughout the paper, which we expect to improve the measurement of competition metrics that rely on full coverage data (eg, industry concentration measures).

In addition to these changes, Fabling and Maré (2019) took steps to improve the average quality of the data, including better screening for data consistency and better editing of the data to repair known quality issues. We expect these quality changes to improve the measurement of regression-based competition metrics, because such metrics are biased towards zero (lower estimated competition) in the presence of measurement error.

[4]The top panel of appendix figure A.1 demonstrates the effect of the choice of unit of observation on the labour Herfindahl-Hirschman Index, where it is feasible to construct both a firm- and group-level metric. Measured competition is often materially lower (HHI higher) in the group-level analysis, particularly for less competitive (high HHI) industries. In essence, it appears that dominant firms are often part of dominant groups of dominant firms. Overall, though, the correlation between the firm- and group-level measures is 0.989. More generally, competition metrics that don't measure industry concentration directly are likely to be less affected by the unit of observation choice.

3.2 Competition metrics

Our desire to relate competition metrics to productivity outcomes restricts the analysis in two ways. Firstly, we must exclude not-for-profit firms, and industries that aren't in Stats NZ's measured sector, since neither of these groups are included in the productivity dataset. This restriction is not particularly problematic for the analysis since the primary exclusion is the government sector. Secondly, we cannot estimate production functions at very detailed level of industry disaggregation, either because we don't have the necessary industry-specific price deflators or because there are insufficient firm-level observations to estimate production functions with sufficient precision (Fabling and Maré 2015b). Furthermore, despite population-weighting, detailed industry competition measures are likely to be susceptible to variation arising from missing data. The productivity dataset classifies firms into one of 39 production function industries and the main analysis in the paper relies on this classification to define a market. The unsatisfactory nature of defining competitors purely using the industry classification has been well described elsewhere (including in Gardiner 2017).[5] However, as in other studies, we have limited alternatives.

To motivate the paper, and to enable some direct comparison to prior MBIE results, we provide some initial statistics at the four-digit (ANZSIC'06) industry level. To avoid issues with small samples we pool the data into two time periods (2001-2008 and 2009-2016) and then group industries at less detailed ANZSIC levels when we have fewer than 200 observations in an industry-time period. This aggregation process results in 318 industries, which is a similar level of disaggregation to the 309 (ANZSIC'96) industries in MBIE (2016).

We consider four common measures of competition following Griffith et al. (2005), implementing two versions of each measure, for a total of eight competition metrics.[6] The dominance and Herfindahl-Hirschman Index

[5]For example, we might be concerned that, at least in some industries, geographic distance inhibits competition. The bottom panel of figure A.1 demonstrates the effect on HHI_L of treating each Urban Area (UA) as a separate market within an industry. This alternative market scope assumption has a stronger impact on measured industry concentration than calculating HHI at the group level (top panel of same figure) because many industries are dispersed across New Zealand. The correlation between firm-level and firm by UA-level HHI measures is 0.797.

[6]Potentially, additional measures are available from the Business Operations Survey (BOS) based on the self-reported question "How would you describe this business's competition?" where possible response categories are "captive market/no effective competition," "no more than one or two competitors," "many competitors, several dominant," "many

(HHI) measures capture the concentration of output (Y) or labour input (L) within an industry. Dominance is defined as the top-twenty firm share of the aggregate

$$\text{Dominance}_{X,jt} = \frac{\sum_{i=1}^{20} X_{ijt}}{\sum_{i=1}^{N_{jt}} X_{ijt}}, X \in \{Y, L\} \tag{1}$$

where firms (i) in industry j and year t are ordered from largest to smallest by X in each industry-year.[7] The choice of how many firms to include in the top group is somewhat arbitrary and, in our case, is driven by the desire to keep the group small, traded off against the need to satisfy Stats NZ's confidentiality requirements. The HHI is the sum of the squared share of each firm in total output/labour, which can be expressed as

$$\text{HHI}_{X,jt} = \frac{\sum_{i=1}^{N_{jt}} X_{ijt}^2}{(\sum_{i=1}^{N_{jt}} X_{ijt})^2}, X \in \{Y, L\}. \tag{2}$$

The other two competition metrics require the calculation of total variable costs, defined as $C = M + W^{\star}$, where $W^{\star}$ is labour costs including imputed labour costs for working proprietors (WPs) as well as employee labour costs from PAYE data.[8] Following Fabling and Maré (2019), WP labour costs are imputed using the year-specific firm-level average employee labour cost (per FTE worker) multiplied by the total WP labour input. This method of imputation excludes WP-only firms, since such firms have no employee labour cost to impute from.[9]

competitors, none dominant," and "don't know." We do not exploit these data as it is difficult to interpret within-industry variation in responses and, therefore, to determine a "representative" value for an industry, and because the BOS does not start until 2005 reducing the amount of data available for a consistent analysis. Additionally, the BOS covers the population of firms with six or more employees, which may be unrepresentative of the broader population we consider (ie, all firms with $L > 0$).

[7] For ease of reading, industry and time indexes are excluded in tables and figures. Population weights are used throughout this paper, and the notation in this section folds the population weighting into the firm index (i) rather than explicitly spelling out the weighting in the formulae. In the case of the top 20 identification, weighting implies that the sum of the weights of the "top" group is 20, rather than there necessarily being 20 actual productivity data observations.

[8] In the productivity dataset, rental, leasing and rates costs are counted as capital services (K), rather than intermediate consumption (M), so that rented and owned capital are treated consistently. This means that the measure of C adopted for this paper differs from the standard definition in the literature, which would normally include rental costs in total variable costs.

[9] Fabling and Maré (2019) tested the feasibility of using an industry-level analogue of the

The first competition metric that uses total variable costs is the average price-cost margin (PCM), defined as

$$\overline{\text{PCM}}_{jt} = \frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} \max\left\{ \frac{Y_{ijt} - C_{ijt}}{Y_{ijt}}, -1 \right\}. \tag{3}$$

Since the PCM is unbounded from below, we impose a lower bound at -1 to avoid a small number of instances where (small) firms with large negative profits relative to output severely skew the industry mean value. The alternative PCM measure weights by output as well as population weighting, and does not require the lower bound constraint, since small firms have limited influence on the estimated value. Weighting by Y is equivalent to calculating the aggregate industry PCM, so we label this variable $\overline{\text{PCM}}_{\text{A}}$, which is

$$\overline{\text{PCM}}_{\text{A},jt} = \frac{1}{\sum_{i=1}^{N_{jt}} Y_{ijt}} \sum_{i=1}^{N_{jt}} \frac{Y_{ijt}(Y_{ijt} - C_{ijt})}{Y_{ijt}} = \frac{\sum_{i=1}^{N_{jt}} (Y_{ijt} - C_{ijt})}{\sum_{i=1}^{N_{jt}} Y_{ijt}}. \tag{4}$$

The final competition metric is the profit elasticity (PE), which is estimated from the following industry-specific equation

$$\ln(Y_{ijt} - C_{ijt}) = \alpha_{j't} + \text{PE}_{\text{OLS},jt} \times \frac{C_{ijt}}{Y_{ijt}} + \epsilon_{ijt} \tag{5}$$

where $\alpha_{j't}$ is a set of four-digit ANZSIC industry-year dummies. This specification follows Griffith et al.'s (2005) empirical implementation of Boone (2008), and captures the responsiveness of profit to variation in costs relative to a reference firm in the industry.[10] In this empirical setting, the cost-output ratio is restricted to the range $[0, 1)$, since negative profit firms are excluded by the logging of the dependent variable.[11]

We expect the profit elasticity to be negative – that is, cost increases reduce profits – and, as with all the competition metrics, associate lower (more negative) values with higher competition (more responsive profit). Since both

firm-level average to impute WP labour costs for WP-only firms. They found that such an approach led to implausibly low mark-up estimates. Conversely, assuming WP labour costs were zero resulted in implausibly high mark-up estimates.

[10] MBIE (2016) include a direct control for (log) firm size in their specification of the profit elasticity, though this doesn't appear to be motivated by the relevant theory. For that reason, we do not include such a term, which presents a confounding factor when comparing results between this study and MBIE's.

[11] MBIE (2016) log the cost-output ratio, which is inconsistent with theory and unnecessary from an empirical perspective because of the bounded nature of the ratio.

the dependent and independent variables are derived from the same base data (Y and C), measurement error will bias estimated PE towards zero, implying less competition than there actually is. On this basis, we expect the quality improvements in the productivity dataset to imply New Zealand markets are "more competitive" than was found in prior analyses.

As an alternative specification, we also estimate PE with firm fixed effects (δ_i)

$$\ln(Y_{ijt} - C_{ijt}) = \alpha_{j't} + \text{PE}_{\text{FE},jt} \times \frac{C_{ijt}}{Y_{ijt}} + \delta_i + \epsilon_{ijt} \tag{6}$$

which, among other things, has the effect of setting the reference firm to be more appropriate in industries where industry grouping does not reflect the appropriate market.[12] The PCM also has this robustness feature in the sense that, even if the industry grouping does not reflect a common market, firm profitability is actually constrained by competitors in the market, even if those competitors are not present in the data (eg, competition with imports). In either case, though, the PCM and PE are being averaged over firms that may not be in the same market. Despite this, we expect $\overline{\text{PCM}}$ and PE_{FE} to be correlated because of this common robustness feature. Similarly, we expect the dominance and HHI measures to be correlated since they all capture concentration in production (outputs or inputs).

Each individual metric measures market power, meaning that higher levels of competition are identified by lower values of the metrics. We calculate eight different competition measures: dominance (in labour or output), HHI (in labour or output), average PCM, aggregate PCM, and profit elasticity (estimated with or without firm fixed effects), expecting these measures to capture different patterns of competition and market power. They are, however, correlated and it would be over-interpreting the differences between them to analyse them individually. To provide a more interpretable set of competition indicators, we derive composite measures, to capture the main distinct patterns of measures. Composite indicators are derived using the method of principal components.

Both the PCM and PE measures result in population restrictions, the impact of which are reflected in table 1. The first three columns of the table show, respectively, the number of firms in the population, the number of firms with employees, and the number of employee firms with positive profit ($Y - C > 0$). The first column matches the population used to measure dominance

[12] Firm-level average population weights are used in the fixed effects estimation so that the weight is constant over time for each firm.

and HHI, while the second and third columns match the population used to estimate PCM and PE respectively.

On average, we lose over half (54%) of productivity-industry firms (the WP-only population) to calculate the PCM using total variable costs, and a further 8 percent of firms are dropped due to negative profit when we calculate the profit elasticity. Dropped firms are, in general, much smaller than retained firms, so that the total loss of labour input (L) is 14 and 23 percent, respectively, for PCM and PE metrics. Following the Global Financial Crisis in 2008/09, there is an overall decline in the number of firms in the population, and the proportion dropped due to negative profit rises to approximately 9% over the 2008-2010 period. The analysis which follows makes no adjustment for selection effects. The final three columns of table 1 report data coverage rates for the three populations, which are increasing over time due to increasing data availability and improvements in raw data quality (enabling more data to be used in the productivity dataset), and which are higher for PCM and PE measures because filing rates are higher for firms with employees (Fabling and Maré 2019).

3.3 Productivity measurement

We rely on multifactor productivity (MFP) to capture industry productivity. In our analysis, we use a revenue-based gross output production function, to allow for the substitutability of labour, capital and intermediate inputs. MFP is estimated at the industry level from an unweighted industry-specific gross output Cobb-Douglas production function with year specific intercepts and firm fixed effects. Firm-level MFP is estimated as the firm fixed effects plus residual from this regression. The use of time-varying, industry-level price deflators for output, capital, and intermediates reduces the impact of changing average industry mark-ups on the productivity measure.

The alternative of using partial productivity measures such as labour productivity has the appeal of providing a measure with meaningful variation across industries but interpretation is confounded by the fact that labour productivity differences will reflect differences in other inputs into production. An industry with higher labour productivity could be more capital intensive, which we would not necessarily want to interpret as more productive. In contrast, MFP provides a measure of productivity that takes into account a firm's use of all inputs, on the basis of an assumed common (industry-specific) production function.

Persistent and large productivity differences between firms within even narrowly defined industries are common (Syverson 2011) and may reflect differences in market power, but could also reflect other unobserved differences between firms. Comparing the productivity of firms within an industry on the basis of an assumed common technology, and defining industry-level competition on the assumption that the firms are competing in a common market, are "...at best just an approximation to a much more complex and changing reality at the firm, product, and factory floor level" (Griliches and Mairesse 1998).

We follow a standard approach in the literature of measuring productivity dispersion as the difference in MFP between the 90th and 10th percentile firm, which has the dual advantages of focussing on the bulk of the distribution of firms, and reducing the susceptibility of the dispersion measure to measurement error, which may be a dominant feature in the tails of the MFP distribution. Since competition may have distinctly different effects on the two tails of the productivity distribution we also, in some specifications, disaggregate productivity dispersion into a contribution above and below the median – that is, into 90th-50th and 50th-10th components.

Finally, we also look at the relative productivity of entering or exiting firms – as well as the firm entry/exit rate – to test for performance-based selection effects in relation to competition. In these specifications, we measure the productivity of entrants (exiters) relative to incumbents and, to avoid potential measurement issues in transition years, we measure entrant (exiter) productivity in the year after entry (prior to exit). For consistency, entry and exit rate regressions exclude the 2016 year, since it is not possible to consistently identify firm exit in 2017 with the available data. For relative MFP entry/exit, we lose a further year of data because of the use of adjacent year MFP.

4 Methods

Our analysis identifies simple correlations between competition metrics and productivity outcomes without attempting to control for endogeneity or omitted factors that might affect both competition and productivity (for example, technological change). This approach is consistent with the way we have estimated firm-level productivity – ie, not controlling for endogenous investment decisions – but leads us to exercise caution when interpreting any findings as identifying causal relationships from increased competition to productivity growth.

The regressions we estimate are all ordinary least squares (OLS) and largely rely on comparing changes in competition with changes in productivity *within* industries. Except for illustrative purposes, we avoid using using cross-industry variation in MFP level, because it is not legitimate to do so (since industries have different production functions).

Within industries, most regressions estimate contemporaneous relationships between competition and productivity, though we report preliminary results using long differences and long lags. Specifically, and using average MFP as a "representative" outcome of interest, we initially estimate the following equations for industry j (one observation per industry):

$$\Delta \mathrm{MFP}_j = \beta \Delta Comp_j + \epsilon_j \tag{T.2}$$

$$\Delta \mathrm{MFP}_j = \beta_{\mathrm{PC1}} \Delta \mathrm{PC1}_j + \beta_{\mathrm{PC2}} \Delta \mathrm{PC2}_j + \beta_{\mathrm{PC3}} \Delta \mathrm{PC3}_j + \epsilon_j \tag{Top T.8}$$

$$\Delta \mathrm{MFP}_j = \beta_{\mathrm{PC1}} \mathrm{PC1}_{j0} + \beta_{\mathrm{PC2}} \mathrm{PC2}_{j0} + \beta_{\mathrm{PC3}} \mathrm{PC3}_{j0} + \epsilon_j \tag{Bottom T.8}$$

where Δ is a long difference (unweighted industry-level average of 2013-2016 values less the unweighted industry level average of 2001-2004 values), the zero time subscript represents initial period (2001-2004) average values, $Comp_j$ is one of the individual competition metrics, PC1-PC3 are principal components of the eight competition metrics, and ϵ_j is the error term. The related table of results for each equation is reported to the right of the equation for reference.

After initially examining long difference relationships, we utilise the annual (t) variation in the data, estimating:

$$\mathrm{MFP}_{jt} = \beta_{\mathrm{PC1}} \mathrm{PC1}_{jt} + \beta_{\mathrm{PC2}} \mathrm{PC2}_{jt} + \beta_{\mathrm{PC3}} \mathrm{PC3}_{jt} + \delta_t + \epsilon_{jt} \tag{Top T.9}$$

$$\mathrm{MFP}_{jt} = \beta_{\mathrm{PC1}} \mathrm{PC1}_{jt} + \beta_{\mathrm{PC2}} \mathrm{PC2}_{jt} + \beta_{\mathrm{PC3}} \mathrm{PC3}_{jt} + \delta_t + \alpha_j + \epsilon_{jt} \tag{Bottom T.9}$$

$$\mathrm{MFP}_{jt} = \sum^{C(j)} \beta^C_{\mathrm{PC1}} \mathrm{PC1}_{jt} + \sum^{C(j)} \beta^C_{\mathrm{PC2}} \mathrm{PC2}_{jt} + \sum^{C(j)} \beta^C_{\mathrm{PC3}} \mathrm{PC3}_{jt} + \delta_t + \alpha_j + \epsilon_{jt} \tag{T.10}$$

$$\mathrm{MFP}_{jt} = \sum^{j} \beta^i_{\mathrm{PC1}} \mathrm{PC1}_{jt} + \sum^{j} \beta^C_{\mathrm{PC2}} \mathrm{PC2}_{jt} + \sum^{j} \beta^i_{\mathrm{PC3}} \mathrm{PC3}_{jt} + \delta_t + \alpha_j + \epsilon_{jt} \tag{T.A.1}$$

where δ_t and α_j are time and industry dummies respectively, and $C(j)$ indexes industry clusters as defined later in the paper.

5 Results

We present results using three different industry aggregations. Initially, we provide a bridge back to the earlier work by MBIE using the two-period, 318 industry dataset. These results motivate the rest of the paper by illustrating how two example metrics give differing views on the relative level of competition in any given industry, and about whether competition has been increasing or decreasing over the past decade and a half. We then turn to the annual 39 productivity industry dataset to compare all competition metrics, and to relate those metrics to productivity outcomes. Finally, we group industries into clusters with similar competition patterns, to identify heterogeneity in the competition-productivity relationship between groups.

5.1 Detailed industry

Figures 1-4 illustrate competition measurement using two of the available metrics and the two-period, 318 industry dataset. In each figure, industries are represented by bubbles whose area is proportionate to the total number of firms in the industry. The metrics we choose are the fixed effects version of the profit elasticity measure ($\mathrm{PE}_{\mathrm{FE}}$) – a variant of which is the preferred measure in MBIE (2016) allowing us to make some comparison to that earlier work – and the industry average of the price-cost margin ($\overline{\mathrm{PCM}}$) which we expect, a priori, to provide a similar perspective on competition.[13]

Figures 1 and 2 shows the distribution of $\mathrm{PE}_{\mathrm{FE}}$ and $\overline{\mathrm{PCM}}$, respectively, in each of the two time periods separately (top two smaller panels), and with the two time periods plotted against each other (bottom larger panel). In the latter case, the dashed line plots constant measured competition across the two eight-year periods. In the case of $\mathrm{PE}_{\mathrm{FE}}$, the predominant pattern is for competition to be increasing over time – which can be seen from the relative density of bubbles sitting below the dashed line in the bottom panel of figure 1 (recalling that higher competition is associated with lower values in each of the competition metrics). In contrast, $\overline{\mathrm{PCM}}$ shows a very static distribution

[13] Aggregate PCM and concentration measures are affected by confidentiality requirements, which can add substantial noise in small populations (exacerbated by the functional form of the HHI) or which require suppression in the case of metrics involving Y. For this reason, we do not include any detailed industry measures here for those metrics. In the later regression analysis, we use the metrics within the secure Datalab environment, meaning we can use the unperturbed data.

of competition, though the top two panels indicate that industries move within that distribution (as can be seen by focussing on the larger industries).

Figures 3 and 4 compare the two metrics in levels and changes, respectively. Consistent with our prediction, the two measures are somewhat consistent in their classification of high and low competition industries, with the (unweighted) correlation between the two measures around 0.5 (figure 3). Since the PCM measure shows no overall apparent trend increase in competition, the correlation in changes is much weaker at 0.19 (figure 4). Overall, in this detailed industry setting, the two measures provide somewhat different lenses on competition, particularly if specific industries are of interest.

This comparison presents somewhat of a conundrum for assessing overall competition trends, without making some judgement as to a "preferred" metric on theoretical or empirical grounds or through a detailed assessment of why the metrics may differ (including data-related reasons). In the subsequent analysis we sidestep this issue by combining metrics into principal components and focussing on the relationship between these composite metrics and productivity outcomes, rather than overall competition trends or trends in specific industries.

MBIE (2016) focussed on a preferred metric – a variant derivation of $\mathrm{PE}_{\mathrm{FE}}$ – reaching the conclusion that there was a tendency toward increasing competition in New Zealand industries (determined using estimated time trends). Comparing our levels estimates to the MBIE results should be done with caution, since there are multiple differences in methodological approach including the use of different firm-level data. Taken at face value, though, our estimates (figure 1, top left panel) produce substantially more negative profit elasticities than MBIEs (2016, figure 2) for a similar time period suggesting increased competition. In part, this difference is likely due to greater measurement error in the dataset that MBIE used, which should serve as a caution against cross-country comparison of results even in the presence of apparently identical empirical specification.

5.2 Production function industries

We now switch to the annual 39 productivity industry dataset to relate competition metrics to productivity outcomes. Figure 5 plots the time variation in this dataset for four of the competition metrics, including the two selected for the 318 industry analysis ($\mathrm{PE}_{\mathrm{FE}}$ and $\overline{\mathrm{PCM}}$) as well as the profit elasticity estimated without firm fixed effects ($\mathrm{PE}_{\mathrm{OLS}}$) and the labour-based top 20 firm dominance metric (Dominance_L). Each panel shows the median (solid line), and 25th and 75th percentile (dashed lines) industry by year.

As before, the fixed effects profit elasticity suggests competition has tended to increase over time (PE_{FE} declining). If anything, the price-cost margin in the 39 industry dataset suggests a general decline in competition ($\overline{\text{PCM}}$ increasing). The dominance metric is stable at the median, but with more uncompetitive and competitive markets moving closer to the median. Finally, PE_{OLS} declines substantially across the distribution following the GFC but, by 2016, has recovered to similar levels as pre-GFC. In the regressions that follow we directly control for the potential confounding factor of the GFC (and other macroeconomic shocks) on the estimated competition measures by including time dummies in regressions.

Reflecting on the prediction that increased competition may raise productivity by truncating the bottom end of the productivity distribution, table 2 reports estimated coefficients from regressions of the long difference in average MFP (column 1) or in average MFP dispersion (column 2), on the long difference in each of the eight competition metrics.[14] Each coefficient in this table reflects a separate regression with one observation per industry, and the long difference is the average over the (unweighted) industry-level average of 2013-2016 values less the unweighted industry-level average of 2001-2004 values. Since higher values of the competition metric imply weaker competition, we expect competition coefficients in the MFP regression to be negative (more competition increases average productivity), and in the MFP dispersion regression to be positive (more competition decreases MFP dispersion). Only one of sixteen coefficients is significantly different from zero (at the 10% level or better) and the expected sign, with increased (HHI) concentration of output associated with lower MFP growth. Aside from PE_{OLS}, all point estimates for MFP dispersion coefficients are the expected sign (though insignicantly different from zero), which suggests that combining the competition metrics into principal components may improve our ability to observe any relationship between competition and productivity. As noted earlier, combining competition metrics into principal components helps us to avoid over-interpreting the differences between them, and provides a way of succinctly capturing the main patterns in the competition data.

[14]MFP growth and level regressions include the estimated industry time trend component since, in the absence of this component, average MFP deviates from zero in a year only due to population-weighting, since the unweighted mean fixed effect and residual are both zero (by construction).

Table 3 shows the correlation matrix underlying the principal components analysis, and table 4 reports principal component (PC) weights for PCs with eigenvalues greater than one. As reflected in the weights,[15] the competition metrics fall into approximately three correlated blocks, the first two of which align with our initial expectations – that the HHI and dominance metrics are all highly correlated (and grouped in PC1), and that $\mathrm{PE}_{\mathrm{FE}}$ and $\overline{\mathrm{PCM}}$ are correlated (and grouped in PC2). The aggregate version of the average price-cost margin ($\overline{\mathrm{PCM}}_{\mathrm{A}}$) is correlated with both these groups, but is more closely related to the main components of PC2. The profit elasticity estimated without fixed effects is only weakly correlated with the other competition metrics, including the fixed effects version of the same metric (correlation of 0.14), indicating that cross-firm variation in profits with respect to costs is important. Given the low correlation with other metrics, $\mathrm{PE}_{\mathrm{OLS}}$ is associated with a distinct principal component (PC3). The principal component analysis thus shows that there are three main patterns of competition measures (explaining 85% of the variation in the data), even though we have calculated eight different measures.

Table 5 provides summary statistics for competition metrics to aid interpretation of regression coefficients. By construction each principal component has mean zero over the entire sample, and normalises the variance of each component to be the respective eigenvalue which, in turn, reflects the relative contribution of that principal component to the overall variation in the competition data. To aid interpretation of patterns in the principal components, we then use cluster analysis to group industries with similar PC values together, allocating industries to a modal grouping where sensible – when the industry is in the same cluster for at least 13 of the 16 years – or an other category where industries move between clusters. Figure 6 plots PC1 against PC2 for each cluster and overall, while table 6 reports PC means by productivity industry (all years pooled) with top quartile values in bold font and bottom quartile values in bold italics.

The resulting clustering suggests four distinct groups of industries. Cluster one (top left panel of figure 6) contains industries such as construction, where both industry concentration (PC1) and margin (PC2) metrics imply markets are competitive. Cluster two includes professional services and other industries which are unconcentrated but have relatively high markups/margins. Cluster three includes the food retailing sector and is relatively concentrated (PC1) but has a mix of high and low mark-up industries. Finally cluster four contains two highly concentrated industries relating to

[15]The largest weight for each competition metric is reported in bold to aid discussion.

transport (II12) and telecommunications (JJ12). Since PC3 is the principal component that adds the least variance, sorting of industries into clusters is not strongly affected by PC3 values.

In table 6, industries are grouped by cluster and then sorted by PC1 since, for that principal component only, weights are almost entirely non-negative implying that higher values are unambiguously associated with lower competition, primarily captured by industry concentration (HHI & dominance).

Aside from providing a descriptive classification of industry competition, this grouping enable a better understanding of the regression results by helping to isolate the variation driving the results in table 2. Specifically, table 7 reports cluster mean long differences in MFP and MFP dispersion, together with long difference growth rates in each of the principal components. From these results, it is apparent that cluster four (transport and telecoms) is an outlier in terms of productivity growth (0.339 compared to an overall average of 0.052), declining productivity dispersion (-0.355 compared to -0.044 overall), and reducing industry concentration (-0.675 versus and overall average of -0.079). These "exceptional" industries drive the apparent relationship between HHI_Y and MFP growth in table 2, which can be seen in table 8 when we replace the individual competition metrics with PCs.

The top panel of table 8 repeats the analysis in table 2, using long differences in PCs instead of individual competition metrics. MFP outcomes are regressed on each PC separately (columns 1-3 & 5-7) and then all PCs simultaneously (columns 4 & 8). We focus on these latter estimates, which produce similar results to the individual PC regressions because, in levels, the PCs are constructed to be uncorrelated with each other. The results using long difference PCs are consistent with the results using individual competition metrics. PC3, which primarily relates to $\mathrm{PE}_{\mathrm{OLS}}$, has significant but incorrectly signed coefficients in each regressions. Other principal components have expected signs, but are insignificantly different from zero.

Alternatively, rather than changes in competition affecting productivity contemporaneously, it may be that the level of competition affects future MFP growth and/or dispersion. We test this hypothesis by regressing long difference MFP changes on initial PC values (2001-2004 averages, labelled "$t = 0$"), with results reported in the bottom panel of table 8. Coefficients on PC1 are now significantly different from zero (at the 1% level), but incorrectly signed implying that initially *more* concentrated industries experience higher productivity growth (column 4) and compression of the productivity distribution (column 8). This result follows from the extreme nature of productivity growth in the cluster 4 industries, which are initially highly concentrated. The coefficient on PC3 ($\mathrm{PE_{OLS}}$) is consistent with competition increasing future productivity growth, though this coefficient is barely significant (at the 10% level) when all PCs are included in the regression (column 4).

These tests are quite stringent, in that we reduce the data to one observation per industry and focus on long differences, removing a large part of the variation in the data. Table 9 relaxes these constraints and reports contemporaneous estimated relationships between productivity and competition metrics using annual observations for each industry. We now also look directly at entry/exit dynamics as a potential explanation of how competition may influence the productivity distribution. Specifically, we decompose MFP dispersion into above and below median contributions (columns 2-4 of table 9), check to see whether competition is related to firm entry and exit rates (columns 5-8), and examine whether entry/exit dynamics are more or less selective on productivity in high competition industries (columns 9-10).

The top and bottom panels of table 9 are separate sets of regressions, with the top panel including year dummies, and the bottom panel regressions including both year and productivity industry dummies. The almost complete absence of significant coefficients in the bottom panel indicates that cross-industry variation is primarily responsible for the identification of coefficients in the top panel. These top panel coefficients with only year dummies are the focus of the discussion – except in the case of average MFP (column 1), where it is not legitimate to compare MFP levels in the absence of industry controls.

As in prior regressions, we expect coefficients on competition metrics to be negative on average MFP levels, and positive in regressions involving MFP dispersion (ie, higher competition increases productivity and reduces dispersion). If stronger competition drives low productivity firms out of markets, we expect PC coefficients to be negative in relative exit MFP regressions, consistent with increasing competition causing greater selection on productivity by raising the threshold productivity level for market participation. Consequently, we also expect PC coefficients to be negative in relative entry regressions – that is, higher initial (relative) productivity is required to enter more competitive markets. The effect of competition on firm entry, exit and churn (=entry+exit) is ambiguous since uncompetitive markets may discourage entry due to incumbent behaviour, but may also encourage entry through lower thresholds for participation and higher expected returns.

From the top panel of table 9, there is some evidence that greater competition is associated with lower productivity dispersion, at least in the case of PC1 and PC2 (columns 2-4). In particular, for PC2 (related most strongly to PE_{FE} and PCM measures) this relationship derives largely from a compression of the bottom end of the productivity distribution in industries with relatively more competition. Higher (PC1 & PC2) competition is also associated with less entry, exit and churn (columns 5-8), consistent with the hypothesis that higher productivity thresholds for participation discourage entry. The net effect of lower entry and exit is to have an economically small (or insignificantly different from zero) relationship between competition and net firm entry. Consistent with PC1 & PC2's relationship with MFP dispersion, and as expected, higher (PC1/PC2) competition is associated with higher relative productivity of exiting firms (column 10). In the case of PC1, more competitive industries also have higher relative entrant productivity (column 9), consistent with the threshold for entry/continuation being higher in such industries, relative to lower competition industries. As in previous results, PC3 coefficients continue to suggest that more competition – measured with PE_{OLS} – increases productivity dispersion, particularly in the lower tail of the productivity distribution (column 4).

5.3 Industry groupings

Since these results are derived largely from cross-industry variation in competition, they may be confounded by pooling industries together that have very different market conditions and, therefore, differing relevance of the competition measures. For example, concentration-based competition metrics may have limited relevance to industries with a high proportion of exporters, or high import competition. To test this hypothesis, we group "similar" industries in two ways. Firstly, we make use of the PC-based modal industry clusters and estimate cluster-specific PC coefficients, thus relaxing the constraint that all industries share a common competition-productivity relationship. We do this recognising that industries with differing patterns of competition across metrics may have different underlying determinants of competition levels (eg, varying importance of localised or international competitors). Secondly, we relax the constraint even further and allow each industry to have a separate coefficient on each principal component and then, post-estimation, group coefficients based on industry characteristics (such as the importance of export or import) that may influence the competition-productivity relationship.

Table 10 shows the results of the first of these tests, with cluster-specific coefficients on principal components (and including industry dummies as in the bottom panel of table 9). In relation to average MFP, cluster 4 (transport and telecoms) has the expected sign on PC1 (significant at the 1% level), reflecting the large decrease in concentration and concurrent growth in MFP discussed earlier for these two industries (table 7). Below-median MFP dispersion (column 4) appears to be lower when competition is higher in each of the four clusters (ie, coefficients are positive), though the relationship is identified from variation in industry concentration (PC1) for clusters one and four, and variation in mark-up (PC2) for clusters 2 and 3. If anything, entry and exit rates appear to be somewhat elevated when industries are more concentrated (four significant positive coefficients on PC1 coefficients for entry/exit, at the 5% level or better). Conversely, the coefficient on PC2 for cluster 1 is negative (and significant at the 1% level), which is inconsistent with expectations.

For clusters 3 and 4 (moderately and highly concentrated industries respectively), periods of lower industry concentration (higher competition) are associated with increased selection on productivity for exiting firms, though exit rates are not elevated (column 8 and 10 coefficients on PC1, respectively). For cluster 3, this relationship between increased competition and exit selection also appears true for mark-up (PC2), though in all three cases coefficients are only marginally significant at the 10% level.

For our second test, we group industries based on industry characteristics and, because of the volume of coefficients to consider, limit the outcomes of interest to five summary measures – average MFP, MFP dispersion (MFP_{9010}), the firm churn rate, and the relative productivity of entrants and exiters (corresponding to columns 1, 2, 6 9 & 10 of table 10 respectively). We jointly estimate industry-specific coefficients on each principal component and then compare these estimated coefficients for different industry groupings. Appendix table A.1 reports these regressions, which include year and industry dummies.

Table 11 itemises the industry group characteristics that we use, additionally reporting the source data for each industry classification and the industries that appear in the top and bottom quartile. In addition to these groupings, in results not reported in the paper, we also separate the data into groups based on average levels of PC1-PC3, and into sectors: primary (including mining), manufacturing, and services. For a given grouping, we focus on patterns in PC coefficients for the top and bottom grouping, looking for consistently signed significant coefficients within a group, which might indicate a strong relationship between a subset of competition metrics and productivity outcomes for a particular type of industry grouping. In particular, grouping by the level of each PC allows us to test for non-linearities in the effect of competition on productivity (eg, an inverted-U relationship).

Overall, we find no convincing evidence of specific industry characteristics where relationships between competition metrics and productivity outcomes are consistently strong. Figure 7 and table 12 present, as an example, the case where industries are grouped by the aggregate capital-labour ratio. Figure 7 plots coefficients on PC1 by industry in the MFP dispersion regression (ie, from table A.1, column 4) where shading indicates both significance and whether the specific industry has a high, moderate or low capital-labour ratio (as itemised in table 11). Counts of significant coefficients by industry group are reported in table 12, where the results in figure 7 correspond to the left quadrant of the second panel in the table.[16] In the case of MFP dispersion, for example, while there is some evidence that increased PC1 competition in high K/L ratio industries is related to reduced MFP dispersion (7 out of 10 coefficients significant and positive), two high K/L industries display the opposite pattern. In the case of the contribution of entry to average MFP, the overall distribution of industry coefficients (bottom row of the third panel in table 12) makes it unlikely that there is an industry grouping that consistently displays the expected relationship between competition and entering firm productivity, since few of the coefficients are the expected negative sign.

6 Conclusions

Overall, our study had two main objectives – to evaluate the quality and usefulness of improved business microdata for the analysis of productivity and competition, and to estimate the relationship between competition and productivity in New Zealand industries. On the first count, we have demonstrated that the updated Fabling-Maré productivity data support meaningful measurement of industry-level competition, providing a range of competition indicators that highlight different aspects of industry competitiveness. Similarly, estimated MFP from within that dataset provides a credible indicator of productivity variation across time and of dispersion across firms within each industry.

[16] The "0" grouping includes coefficients that are insignificantly different from zero at the 10% level.

We have been less successful in deriving statistically significant evidence of a relationship between competition and productivity over the sample period. This lack of evidence does not necessarily imply that competition and productivity are unrelated. We interpret our findings as reflecting that changes in competition over the sample period have not been particularly pronounced, making it difficult to identify a systematic relationship. Any effect of competition changes on firm productivity is masked by other sources of time variation in productivity.

In principle, the absence of clear results may also relate to the fact that there may be different types of uncompetitiveness, which the various competition metrics identify some aspects of, but not others. Some industries may have fixed costs (of entry), while others may have transitory rents or high rates of innovation. Other markets may be highly heterogeneous such that their boundaries exceed the industry boundaries or are localised or international. The principal components approach, coupled with the disaggregation of industries into various groupings, is intended to address this issue, and we find some evidence of truncation of the productivity distribution below the median when competition is greater, in part due to greater selection-to-exit on productivity when competition is higher. A direct positive correlation between competition and productivity growth exists in highly concentrated industries (transport and telecommunications) but, given the extreme growth in MFP, we suspect this relationship may be driven by other factors such as technological change, rather than arising directly from reductions in industry concentration.

It should also be noted that the productivity and competition measures that we use are all subject to some imprecision due to the nature of the data, measurement and estimation. The estimated individual competition measures are subject to relatively strong transitory fluctuations, with increase in one year often followed by declines. This problem is reduced by the use of principal components, but it is still present, making interpretation of year-to-year changes challenging. The impact of such imprecision is limited when the measures are used as indicators of the level of competition or productivity. However, when examining changes, especially over relatively short periods or when underlying true changes are small, patterns should be interpreted cautiously. In such cases, random fluctuations may account for much of the estimated variation over time.

This conclusion, together with our empirical analysis of the correlation between metrics and their differing views on trends in industry competition point to a broader issue. Specifically, it may be hard to reach clear conclusions about the state of competition in New Zealand without taking a strong stance on a preferred set of competition metrics and, by extension, a clear view on which metrics (if any) capture the aspects of competition that matter most to policy outcomes such as productivity growth.

Internationally, the strongest evidence of a positive relationship between competition and productivity derives from studies that analyse industries or countries over periods when there were substantial identifiable changes in competition. The empirical literature, as summarised by CMA (2015) and Holmes and Schmitz (2010), includes studies of:

- Periods of pronounced and widespread economic reforms (UK 1979-82), using a panel of industries (Haskel 1991) or firms (Disney et al. 2003; Nickell 1996);
- Deregulation, privatisation or liberalisation in specific industries: US telecommunication (Olley and Pakes 1996); electricity (Jamasb et al. 2005; Maher and Wise 2005); road freight (Boylaud and Nicoletti 2003); or air transport (Micco and Serebrisky 2006);
- Introduction of railroads in the US (Holmes and Schmitz 2001);
- Competition from a large new entrant to a market such as iron ore (Schmitz 2005) or retail (Matsa 2011); and
- Increased exposure to international competition from trade liberalization (De Loecker 2011).

New Zealand's economic reforms of the 1980s represented a significant change in competition as a result of deregulation, trade liberalisation, and the removal of various forms of subsidisation (Evans et al. 1996). Consistent with other international studies of major reform periods, previous studies of this period have documented some links between market competitiveness and subsequent productivity growth. Färe et al. (2002) found sustained productivity improvements in the primary sector as a result of the 1980s reforms which increased competitiveness, but only relatively short term positive impacts on productivity in manufacturing.

For our study period, change in competition and in productivity has been less pronounced, making it difficult to separate the impact of competition on productivity from other changes that have potentially affected competition or productivity.

6.1 Future directions for research & analysis

Using the methods outlined in this paper, the LBD will continue to be a good source for monitoring competition change and productivity growth. Although there is some scope for analysing competition and productivity trends for more detailed industries, the size of some New Zealand industries limits the statistical reliability of the estimated measures. Furthermore, where the number of firms in an industry is small, or activity is highly concentrated, confidentiality restrictions may preclude the release of statistics for exactly the industries that are of most interest to competition policy agencies.

Thus, while administrative data is useful as a source of monitoring information at the industry level, it will never be a complete substitute for more focused investigations into competitive practices within industries of interest. In part, this is because administrative microdata compiled by Stats NZ can only be used for research – not regulatory – purposes, and cannot be used to identify individual firms. Therefore, while the microdata may suggest industries featuring uncompetitive behaviour, other sources of data and approaches (eg, case studies) will continue to be needed if such behaviours are to be explicitly identified.

The LBD could be used to investigate mechanisms by which competition may affect productivity. CMA (2015) summarise studies that have addressed the question of "why might stronger competition lead to higher productivity." While we have looked at whether there are heterogeneous effects of competition on productivity related to industry differences in the capital-labour ratio, R&D investment and innovation outcomes, finding little in the way of statistically significant patterns, it may be worth focusing on particular industries where there have been pronounced changes in these characteristics to see whether these changes are linked to competition (and productivity).

Along similar lines, cross-sectional variation in competitiveness/market power could be used in conjunction with Business Operations Survey data to examine the relationship between competition and a range of potentially productivity-enhancing practices, including management (as in Bloom and Van Reenen 2010); business strategy, skills and skills acquisition; employment practices; wage and price-setting practices; and responses to regulation. Some elements of these BOS data, most notably the management practices modules, have a strong panel element enabling the possibility of linking changes in competition to changes in (productivity-enhancing) business practices.

Finally, the effect of competition on non-productivity outcomes could also be investigated. The LBD and broader IDI are particularly well placed to look at the impact on labour markets, and a focus on this outcome would overcome some of the limitations of a productivity focus. Specifically, wage and salary data is full coverage, enabling a more finely detailed industry level analysis. Data could also support the analysis of competition in the labour market, rather than the product market competition that has been the focus of the current paper. The movement of workers between firms also provides an alternative lens for thinking about wage impacts of competition and, more broadly, rent-sharing between workers and firms.

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Tables

Table 1: Coverage of competition measures for productivity population industries

	Total firms (weighted)			Proportion of population				Data coverage rate		
	Pop	PCM	PE	Firms		L		Pop	PCM	PE
	(L > 0)	(FTE > 0)	($Y - C > 0$)	PCM	PE	PCM	PE	(L > 0)	(FTE > 0)	($Y - C > 0$)
2001	296,532	127,764	106,236	0.431	0.358	0.832	0.750	0.611	0.675	0.681
2002	295,029	129,657	108,669	0.439	0.368	0.839	0.762	0.616	0.676	0.682
2003	298,863	133,275	111,045	0.446	0.372	0.844	0.765	0.626	0.692	0.698
2004	303,429	137,394	114,321	0.453	0.377	0.851	0.768	0.632	0.698	0.705
2005	306,174	141,414	117,657	0.462	0.384	0.857	0.781	0.636	0.700	0.706
2006	310,563	144,450	118,545	0.465	0.382	0.860	0.775	0.641	0.702	0.709
2007	312,711	146,082	119,421	0.467	0.382	0.861	0.767	0.643	0.706	0.713
2008	314,004	147,714	120,219	0.470	0.383	0.863	0.772	0.654	0.713	0.720
2009	309,690	144,402	115,464	0.466	0.373	0.861	0.757	0.655	0.713	0.721
2010	302,679	138,546	111,645	0.458	0.369	0.857	0.752	0.661	0.723	0.730
2011	302,520	137,409	112,956	0.454	0.373	0.858	0.770	0.669	0.730	0.738
2012	300,405	137,037	113,493	0.456	0.378	0.860	0.757	0.671	0.734	0.741
2013	299,472	137,646	114,258	0.460	0.382	0.862	0.772	0.680	0.739	0.744
2014	299,595	139,311	118,128	0.465	0.394	0.867	0.782	0.694	0.751	0.757
2015	298,008	142,206	121,473	0.477	0.408	0.873	0.777	0.691	0.741	0.746
2016	295,569	144,582	121,833	0.489	0.412	0.880	0.778	0.670	0.701	0.708
Total	**4,845,243**	**2,228,889**	**1,845,363**	**0.460**	**0.381**	**0.858**	**0.768**	**0.653**	**0.713**	**0.719**

The price-cost margin (PCM) and profit elasticity (PE) measures require an estimate of total variable costs (C), which involves imputing WP labour costs from employee labour costs for firms that have both types of labour. In the absence of a good imputation method for WP labour costs in WP-only firms, those firms are excluded from the PCM and PE measures. Additionally, because the left-hand side variable in the estimation of PE is $\ln(Y - C)$ we lose observations for that metric where $Y - C \leq 0$ (ie, loss-making firms).

Table 2: Long difference estimates of relationship between MFP and competition – individual metrics

	(1) ΔMFP	(2) $\Delta \mathrm{MFP}_{9010}$
$\Delta \mathrm{PE}_{\mathrm{OLS}}$	0.074**	-0.092***
	[0.032]	[0.025]
$\Delta \mathrm{PE}_{\mathrm{FE}}$	-0.024	0.077
	[0.058]	[0.101]
$\Delta \overline{\mathrm{PCM}}$	0.305	0.171
	[0.790]	[1.501]
$\Delta \overline{\mathrm{PCM}}_{\mathrm{A}}$	-0.426	0.015
	[0.505]	[0.538]
$\Delta \mathrm{Dominance}_L$	-0.198	0.437
	[0.506]	[0.608]
$\Delta \mathrm{Dominance}_Y$	-0.250	0.633
	[0.281]	[0.475]
$\Delta \mathrm{HHI}_L$	0.235	0.733
	[3.513]	[3.832]
$\Delta \mathrm{HHI}_Y$	-1.328**	0.569
	[0.489]	[0.465]
N(observations)	39	39

Each reported coefficient is estimated from a separate OLS regression with one observation per productivity industry. In these regressions, MFP includes an industry time trend component. Long difference is unweighted industry-level average of 2013-2016 values less the unweighted industry-level average of 2001-2004 values. Robust standard errors reported in brackets. Stars indicate coefficients are significantly different from zero at the 1% (***), 5% (**) or 10% (*) level.

Table 3: Correlation between competition metrics

	$\mathrm{PE}_{\mathrm{OLS}}$	$\mathrm{PE}_{\mathrm{FE}}$	$\overline{\mathrm{PCM}}$	$\overline{\mathrm{PCM}}_{\mathrm{A}}$	Dom_L	Dom_Y	HHI_L
$\mathrm{PE}_{\mathrm{FE}}$	0.138						
$\overline{\mathrm{PCM}}$	0.127	0.640					
$\overline{\mathrm{PCM}}_{\mathrm{A}}$	-0.112	0.662	0.604				
$\mathrm{Dominance}_L$	0.027	0.111	0.006	0.351			
$\mathrm{Dominance}_Y$	0.017	0.030	-0.011	0.306	0.906		
HHI_L	-0.018	0.167	-0.053	0.234	0.773	0.641	
HHI_Y	-0.091	0.128	-0.059	0.234	0.751	0.719	0.934

Correlations based on 39 productivity industries over 16 years (624 observations).

Table 4: Principal component weights

	PC1	PC2	PC3	Proportion explained
PE_{OLS}	-0.011	0.097	**0.961**	0.985
PE_{FE}	0.172	**0.563**	0.043	0.788
$\overline{\text{PCM}}$	0.085	**0.593**	0.033	0.784
$\overline{\text{PCM}}_{\text{A}}$	0.272	**0.484**	-0.246	0.830
Dominance_L	**0.487**	-0.121	0.079	0.881
Dominance_Y	**0.457**	-0.147	0.073	0.794
HHI_L	**0.468**	-0.151	0.029	0.831
HHI_Y	**0.474**	-0.171	-0.039	0.863
Proportion explained	0.445	0.269	0.131	0.845
Eigenvalue	3.560	2.152	1.046	

All principal components with eigenvalues greater than one reported (PC4 has an eigenvalue of 0.562, explaining a further 7% of the total variation). Bold font indicates highest weight for each contributing competition metric. Principal components based on 39 productivity industries over 16 years (624 observations).

Table 5: Summary statistics – competition metrics and principal components

	Mean	Standard deviation
PE_{OLS}	-4.478	0.754
PE_{FE}	-5.474	0.914
$\overline{\text{PCM}}$	0.152	0.057
$\overline{\text{PCM}}_{\text{A}}$	0.229	0.099
Dominance_L	0.317	0.224
Dominance_Y	0.429	0.257
HHI_L	0.025	0.048
HHI_Y	0.065	0.109
PC1	0.000	1.887
PC2	0.000	1.467
PC3	0.000	1.023

Summary statistics based on 39 productivity industries over 16 years (624 observations). Principal component weights reported in table 4.

Table 6: Mean of principal components by productivity industry

	Industry	PC1	PC2	PC3
		Cluster 1		
EE13	Construction services	***-2.221***	-1.061	-0.472
EE11	Building construction	***-1.955***	***-1.856***	**1.397**
RS21	Other serv.	***-1.750***	-0.180	***-0.617***
AA11	Horticulture & fruit growing	***-1.709***	***-1.205***	***-0.873***
CC91	Furniture & other manu.	***-1.679***	***-1.724***	***-0.794***
GH21	Accommodation & food serv.	***-1.475***	-0.075	***-0.705***
AA14	Poultry, deer & other stock farming	***-1.399***	-0.355	-0.352
MN21	Administrative & support serv.	-1.204	-0.617	**0.674**
CC7	Metal & metal product manu.	-0.925	***-1.498***	0.038
CC21	Textile, leather, cloth & footwear manu.	-0.913	***-1.549***	**0.847**
CC82	Machinery & other equipment manu.	-0.906	-0.879	**0.587**
CC81	Transport equipment manu.	-0.690	***-1.334***	**0.619**
CC3	Wood & paper product manu.	-0.652	***-2.278***	0.219
		Cluster 2		
AA13	Dairy cattle farming	***-1.334***	**2.626**	-0.490
MN11	Professional, scientific & tech. serv.	***-1.282***	**1.390**	0.247
FF11	Wholesale trade	-1.112	**1.312**	-0.251
II11	Road transport	-1.016	0.942	-0.167
GH11	Motor vehicle/parts & fuel retailing	-0.695	1.030	0.515
AA31	Fishing & aquaculture	-0.523	**1.317**	-0.460
GH13	Other store-based & non-store retailing	-0.418	**1.398**	-0.451
KK13	Auxiliary finance & insurance serv.	-0.275	**1.774**	**0.873**
LL11	Rental & hiring serv.	0.674	**2.985**	-0.379
		Cluster 3		
CC1	Food & beverage manu.	0.482	***-2.182***	***-0.690***
CC5	Petrochemical product manu.	0.573	-0.013	**1.292**
RS11	Arts & recreation serv.	0.736	**1.272**	***-0.593***
II13	Post, courier support & warehouse serv.	**0.845**	0.645	**1.598**
EE12	Heavy & civil engineering construction	**0.875**	-0.927	**1.673**
GH12	Supermarket, grocery & spec. food retailing	**1.054**	**1.362**	-0.331
JJ11	Information media serv.	**1.163**	-0.256	-0.293
CC61	Non-metallic mineral product manu.	**1.475**	***-1.256***	***-0.510***
DD1	Electricity, gas & water	**2.321**	0.744	***-0.769***
BB11	Mining	**2.599**	1.174	***-0.909***
KK1_	Finance, insurance & real estate	**3.304**	**1.292**	0.112
		Cluster 4		
II12	Rail, water, air & other transport	**5.804**	***-2.548***	0.141
JJ12	Telecom., internet & library serv.	**5.834**	-0.752	-0.344
		Other (no predominant cluster)		
AA12	Sheep, beef cattle & grain farming	***-1.786***	0.415	***-0.963***
AA32	Agri., forest, fish support serv. & hunting	-1.270	0.516	-0.098
CC41	Printing	-0.421	-0.155	**0.866**
AA21	Forestry & logging	-0.129	0.505	-0.190

Industry level mean is unweighted average over all 16 years (2001-2016). Principal component weights reported in table 4. Industries grouped by modal PC-based cluster, and then ordered by PC1 with larger values generally indicating more concentrated (less competitive) industries. Where the modal cluster does not constitute at least 13 (out of 16) annual observations, the industry is classified to "other." The top (bottom) quartile of principal component values are in bold (bold italic) font.

Table 7: Mean of long difference variables by PC-based cluster

	Mean				
	ΔMFP	ΔMFP_{9010}	ΔPC1	ΔPC2	ΔPC3
Cluster 1	0.023	0.011	-0.067	-0.153	-0.033
Cluster 2	0.065	-0.032	-0.056	-0.242	-0.469
Cluster 3	0.031	-0.065	0.005	-0.118	0.392
Cluster 4	0.399	-0.355	-0.675	-0.191	0.802
Other (no predominant cluster)	0.004	-0.035	-0.106	-0.004	-0.246
Total	**0.052**	**-0.044**	**-0.079**	**-0.150**	**0.007**

MFP includes an industry time trend component. Long difference is unweighted industry-level average of 2013-2016 values less the unweighted industry-level average of 2001-2004 values. Industries grouped by PC-based modal cluster as summarised in table 6.

Table 8: Long difference estimates of relationship between MFP and competition – principal components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A) Change on change	ΔMFP				ΔMFP_{9010}			
ΔPC1	-0.115			-0.085	0.096			0.055
	[0.069]			[0.068]	[0.075]			[0.083]
ΔPC2		0.005		-0.001		-0.001		0.013
		[0.027]		[0.024]		[0.049]		[0.054]
ΔPC3			0.056**	0.046*			-0.062***	-0.058**
			[0.025]	[0.023]			[0.017]	[0.025]
N(observations)	39	39	39	39	39	39	39	39
Adjusted R^2	0.064	-0.027	0.090	0.087	0.019	-0.027	0.078	0.045
(B) Change on initial level	ΔMFP				ΔMFP_{9010}			
$PC1_{t=0}$	0.034***			0.029***	-0.046***			-0.046***
	[0.011]			[0.011]	[0.014]			[0.014]
$PC2_{t=0}$		-0.006		-0.005		0.013		0.011
		[0.019]		[0.015]		[0.023]		[0.015]
$PC3_{t=0}$			-0.045**	-0.030*			0.022	-0.001
			[0.020]	[0.016]			[0.015]	[0.020]
N(observations)	39	39	39	39	39	39	39	39
Adjusted R^2	0.200	-0.023	0.079	0.203	0.277	-0.013	-0.009	0.244

Top and bottom panels are separate sets of regressions. In these regressions, MFP includes an industry time trend component. Long difference is unweighted industry-level average of 2013-2016 values less the unweighted industry-level average of 2001-2004 values (ie, one observation per industry). Bottom panel regressions have initial period (2001-2004, denoted "$t = 0$") principal component values as the right-hand side variable. Principal component weights reported in table 4. Robust standard errors reported in brackets. Stars indicate coefficients are significantly different from zero at the 1% (***), 5% (**) or 10% (*) level.

Table 9: Estimated relationship between MFP dispersion, entry/exit dynamics and competition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		MFP dispersion			Firm entry/exit rate				Relative MFP	
	MFP	MFP_{9010}	MFP_{9050}	MFP_{5010}	Net entry	Churn	Entry	Exit	Entry	Exit
(A) With year dummies										
PC1		0.074	0.043**	0.031	0.003***	0.015***	0.009***	0.006***	-0.011*	-0.018***
		[0.044]	[0.021]	[0.030]	[0.001]	[0.003]	[0.002]	[0.001]	[0.006]	[0.004]
PC2	N/A	0.123***	0.049**	0.074**	0.001	0.009**	0.005*	0.004**	0.000	-0.012*
		[0.044]	[0.020]	[0.030]	[0.001]	[0.004]	[0.002]	[0.002]	[0.010]	[0.007]
PC3		-0.097**	-0.013	-0.084**	0.001	0.004	0.002	0.002	0.011	0.015
		[0.047]	[0.017]	[0.034]	[0.002]	[0.006]	[0.004]	[0.003]	[0.011]	[0.010]
N(observations)	624	624	624	624	585	585	585	585	507	507
Adjusted R^2	0.104	0.150	0.202	0.104	0.159	0.330	0.323	0.276	0.022	0.103
(B) With year and industry dummies										
PC1	-0.045	0.020	0.016	0.004	0.001	0.011	0.006	0.005	0.019	-0.034
	[0.030]	[0.033]	[0.018]	[0.029]	[0.007]	[0.007]	[0.006]	[0.004]	[0.027]	[0.024]
PC2	0.010	0.002	-0.012	0.015	0.006**	-0.004	0.001	-0.005**	0.003	-0.009
	[0.010]	[0.018]	[0.011]	[0.011]	[0.003]	[0.004]	[0.002]	[0.002]	[0.013]	[0.012]
PC3	0.009	-0.009	0.001	-0.010	-0.002	0.003	0.001	0.002*	0.009	0.020
	[0.007]	[0.011]	[0.006]	[0.009]	[0.001]	[0.002]	[0.001]	[0.001]	[0.009]	[0.015]
N(observations)	624	624	624	624	585	585	585	585	507	507
Adjusted R^2	0.589	0.980	0.961	0.967	0.517	0.919	0.877	0.842	0.549	0.422

Top and bottom panels are separate sets of regressions – top panel regressions include year dummies, and bottom panel regressions include year and industry dummies. Coefficients estimated on dataset with 39 productivity industries over 16 years (624 observations). In column (1), MFP includes an industry time trend component, and coefficients are not estimated in specifications without industry dummies. For consistency, entry and exit rate regressions exclude the 2016 year, since it is not possible to consistently identify firm exit in 2017 with the available data. For relative MFP entry/exit, we lose a further year of data because of the use of adjacent year MFP. MFP is relative to incumbent firms, and single-year firms (entrant-exiters) are excluded. Robust standard errors (clustered on industry) reported in brackets. Stars indicate coefficients are significantly different from zero at the 1% (***), 5% (**) or 10% (*) level.

Table 10: Estimated relationship between MFP dispersion, entry/exit dynamics and competition – by cluster

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		MFP dispersion			Firm entry/exit rate				Relative MFP	
	MFP	MFP_{9010}	MFP_{9050}	MFP_{5010}	Net entry	Churn	Entry	Exit	Entry	Exit
PC1										
Cluster 1	0.028	0.201	0.010	0.192*	0.019	0.022	0.020**	0.002	0.198***	-0.095
	[0.090]	[0.131]	[0.041]	[0.106]	[0.012]	[0.014]	[0.009]	[0.009]	[0.068]	[0.062]
Cluster 2	-0.052	-0.130	-0.005	-0.125	-0.035*	0.043**	0.004	0.039**	-0.039	-0.023
	[0.113]	[0.092]	[0.030]	[0.088]	[0.019]	[0.020]	[0.012]	[0.016]	[0.040]	[0.078]
Cluster 3	-0.017	-0.044	-0.020	-0.024	-0.007	-0.008	-0.008	-0.001	-0.036	-0.054*
	[0.025]	[0.034]	[0.029]	[0.037]	[0.010]	[0.008]	[0.006]	[0.007]	[0.049]	[0.030]
Cluster 4	-0.152***	0.070	0.013	0.057*	0.027***	0.024*	0.025**	-0.001	0.037	-0.049*
	[0.019]	[0.051]	[0.022]	[0.029]	[0.007]	[0.013]	[0.010]	[0.003]	[0.040]	[0.028]
Other	-0.037	0.061	0.092***	-0.030	-0.015***	0.011	-0.002	0.013***	0.064	0.027
	[0.028]	[0.042]	[0.013]	[0.031]	[0.002]	[0.007]	[0.004]	[0.003]	[0.041]	[0.042]
PC2										
Cluster 1	0.031	-0.042*	0.010	-0.052***	0.008	-0.001	0.004	-0.005	-0.049	0.024
	[0.023]	[0.022]	[0.017]	[0.017]	[0.005]	[0.005]	[0.004]	[0.003]	[0.037]	[0.023]
Cluster 2	-0.010	0.065**	0.006	0.059**	0.014**	-0.010***	0.002	-0.012***	0.023	0.011
	[0.037]	[0.030]	[0.012]	[0.029]	[0.006]	[0.004]	[0.004]	[0.003]	[0.017]	[0.010]
Cluster 3	0.016	0.001	-0.033	0.034*	0.000	-0.016*	-0.008	-0.008	0.021	-0.075*
	[0.018]	[0.016]	[0.020]	[0.018]	[0.005]	[0.009]	[0.005]	[0.005]	[0.033]	[0.038]
Cluster 4	-0.046	-0.098	-0.022	-0.076	-0.003	0.000	-0.002	0.002	-0.014	-0.053
	[0.096]	[0.143]	[0.034]	[0.109]	[0.007]	[0.002]	[0.003]	[0.005]	[0.086]	[0.118]
Other	0.011	-0.038*	-0.038***	0.000	0.005***	0.002	0.004	-0.002	-0.014	0.010
	[0.013]	[0.020]	[0.011]	[0.010]	[0.002]	[0.005]	[0.003]	[0.003]	[0.013]	[0.022]
PC3										
Cluster 1	-0.021*	0.011	0.002	0.009	-0.003*	0.001	-0.001	0.002*	0.021	0.007
	[0.012]	[0.013]	[0.008]	[0.009]	[0.001]	[0.002]	[0.001]	[0.001]	[0.014]	[0.012]
Cluster 2	0.065***	-0.074***	-0.016***	-0.057**	-0.006	0.008***	0.001	0.007**	0.021	0.013
	[0.022]	[0.023]	[0.006]	[0.025]	[0.006]	[0.002]	[0.003]	[0.003]	[0.014]	[0.009]
Cluster 3	0.001	-0.009	0.009	-0.018*	0.000	0.006*	0.003*	0.003	-0.007	0.042
	[0.005]	[0.010]	[0.007]	[0.009]	[0.001]	[0.004]	[0.002]	[0.002]	[0.017]	[0.034]
Cluster 4	0.026	0.013	-0.015	0.028	0.000	-0.002	-0.001	-0.001	0.031*	0.029***
	[0.023]	[0.058]	[0.020]	[0.037]	[0.003]	[0.005]	[0.001]	[0.004]	[0.017]	[0.003]
Other	0.010*	-0.003	0.011	-0.013	-0.003	-0.001	-0.002	0.001*	-0.004	-0.007
	[0.005]	[0.021]	[0.007]	[0.016]	[0.002]	[0.002]	[0.002]	[0.001]	[0.027]	[0.022]
N(observations)	624	624	624	624	585	585	585	585	507	507
Adjusted R^2	0.628	0.981	0.964	0.970	0.545	0.926	0.887	0.851	0.555	0.430

All regressions include year and industry dummies. Coefficients estimated on dataset with 39 productivity industries over 16 years (624 observations), grouped by PC-based modal cluster as summarised in table 6. In column (1), MFP includes an industry time trend component. For consistency, entry and exit rate regressions exclude the 2016 year, since it is not possible to consistently identify firm exit in 2017 with the available data. For relative MFP entry/exit, we lose a further year of data because of the use of adjacent year MFP. MFP is relative to incumbent firms, and single-year firms (entrant-exiters) are excluded. Robust standard errors (clustered on industry) reported in brackets. Stars indicate coefficients are significantly different from zero at the 1% (***), 5% (**) or 10% (*) level.

Table 11: Characteristics for grouping industry-specific principal component regression coefficients

Industry characteristic	Source	Top 10 industries	Bottom 10 industries
Domestic tradeability (based on observed proximity to customers)	Conway and Zheng (2014)	AA12 AA13 AA21 AA31 AA32 BB11 CC1 CC5 CC91 JJ12	AA14 EE11 EE12 GH11 GH12 GH21 II11 II12 RS11 RS21
Import share of inputs	Input-output tables	AA14 AA31 CC21 CC5 CC7 CC81 CC82 CC91 II12 JJ11	AA21 AA32 BB11 DD1 EE11 GH12 GH13 II13 KK13 KK1_
Export share of outputs	Input-output tables	AA11 BB11 CC1 CC21 CC3 CC81 CC82 CC91 GH21 II12	AA13 AA32 CC61 DD1 EE11 EE12 EE13 II11 KK13 KK1_
Household share of outputs	Input-output tables	CC1 CC91 FF11 GH11 GH12 GH13 GH21 JJ12 RS11 RS21	AA12 AA13 AA31 AA32 BB11 CC7 EE11 EE12 EE13 KK13
Share of employees with higher qualifications	Census	CC5 DD1 FF11 JJ11 JJ12 KK13 KK1_ MN11 MN21 RS11	AA21 AA31 AA32 CC3 CC7 CC81 EE11 EE13 GH11 II11
Share of employees in skilled occupations	Census	AA13 CC41 CC81 CC91 EE11 EE13 JJ11 JJ12 MN11 RS21	AA21 AA31 AA32 CC1 CC21 GH12 GH13 II11 II13 MN21
Aggregate Y/L	Productivity dataset	BB11 CC1 CC3 CC5 CC7 DD1 EE11 EE12 II12 JJ12	AA11 CC91 GH11 GH12 GH13 GH21 MN11 MN21 RS11 RS21
Aggregate K/L	Productivity dataset	AA12 AA13 AA31 BB11 CC5 DD1 II12 II13 JJ12 LL11	CC21 CC81 CC82 CC91 EE11 EE13 KK13 MN11 MN21 RS21
Aggregate intangibles/L	Productivity dataset	AA31 CC1 CC5 CC61 DD1 JJ11 JJ12 KK13 KK1_ LL11	AA11 AA12 AA13 AA14 AA32 CC21 EE11 EE13 GH11 II11
Share of firms with Auckland, Wellington or Christchurch locations	Labour dataset	CC21 CC41 CC5 FF11 JJ11 JJ12 KK13 KK1_ MN11 MN21	AA11 AA12 AA13 AA14 AA21 AA31 AA32 BB11 CC3 II12
Median firm employment size (excluding WP-only firms)	Labour dataset	CC1 CC3 CC41 CC5 CC61 CC7 CC81 CC82 EE12 GH11	AA12 AA14 AA31 EE11 JJ11 JJ12 KK13 KK1_ MN21 RS11
Share of firms innovating (one-year, annual metric)	Business Operations Survey	CC1 CC41 CC5 CC82 CC91 FF11 II12 JJ11 JJ12 KK1_	AA11 AA12 AA13 AA14 AA21 AA31 AA32 EE11 GH11 RS21
Share of firms doing research & development	Business Operations Survey	AA31 CC1 CC21 CC5 CC61 CC81 CC82 CC91 JJ12 MN11	AA32 EE11 EE12 GH11 GH12 GH13 GH21 II11 II13 RS21
Share of firms whose main market is local	Business Operations Survey (2008)	AA32 CC41 DD1 EE11 EE13 GH11 GH12 GH13 II11 RS21	AA11 AA12 AA13 AA14 CC21 CC5 CC82 FF11 II12 JJ12
Share of firms whose main competition is international	Business Operations Survey (2008)	AA11 AA13 BB11 CC1 CC21 CC5 CC81 CC82 CC91 II12	AA32 EE11 EE12 EE13 GH11 GH13 GH21 II11 RS11 RS21
Share of firms whose products involve substantial customisation	Business Operations Survey (2008)	CC21 CC3 CC41 CC61 CC7 CC81 CC82 CC91 II12 MN11	AA12 AA13 AA14 AA21 DD1 GH11 GH13 GH21 KK1_ LL11

Top and bottom 10 industries are listed alphabetically by industry coding, not by the level of the industry characteristic.

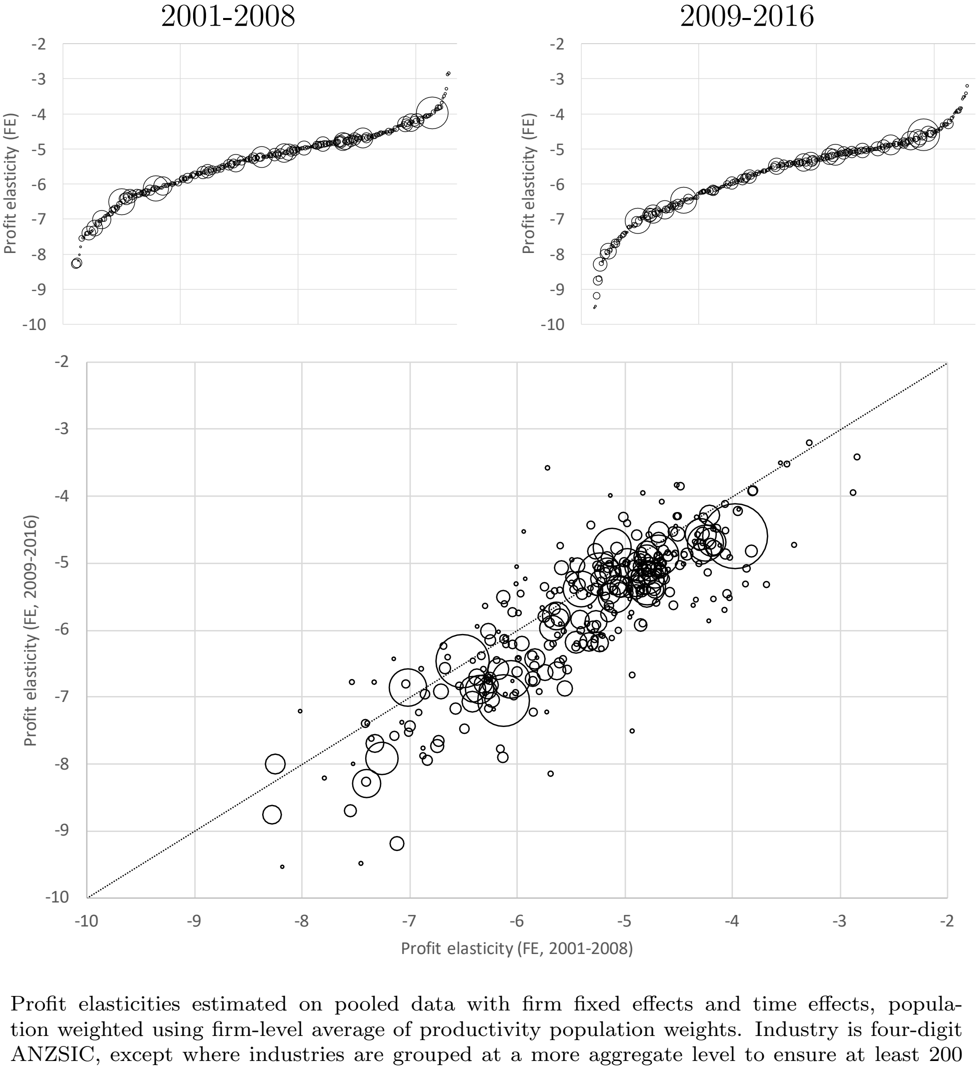
Table 12: Estimated sign of industry-specific principal component coefficients, by aggregate industry capital-labour ratio

MFP									
	PC1			PC2			PC3		
K/L ratio	+	0	-	+	0	-	+	0	-
High	1	3	6	4	2	4	5	1	4
Moderate	5	12	2	6	10	3	6	7	6
Low	0	7	3	5	5	0	1	6	3
Total	**6**	**22**	**11**	**15**	**17**	**7**	**12**	**14**	**13**
MFP dispersion									
	PC1			PC2			PC3		
K/L ratio	+	0	-	+	0	-	+	0	-
High	7	1	2	1	4	5	4	2	4
Moderate	3	12	4	5	8	6	8	6	5
Low	2	6	2	1	8	1	3	5	2
Total	**12**	**19**	**8**	**7**	**20**	**12**	**15**	**13**	**11**
Firm churn rate									
	PC1			PC2			PC3		
K/L ratio	+	0	-	+	0	-	+	0	-
High	6	2	2	1	3	6	6	1	3
Moderate	8	5	6	7	6	6	7	11	1
Low	1	7	2	1	7	2	3	6	1
Total	**15**	**14**	**10**	**9**	**16**	**14**	**16**	**18**	**5**
Relative entry MFP									
	PC1			PC2			PC3		
K/L ratio	+	0	-	+	0	-	+	0	-
High	2	6	2	4	4	2	5	3	2
Moderate	7	7	5	4	7	8	8	7	4
Low	2	5	3	3	6	1	4	3	3
Total	**11**	**18**	**10**	**11**	**17**	**11**	**17**	**13**	**9**
Relative exit MFP									
	PC1			PC2			PC3		
K/L ratio	+	0	-	+	0	-	+	0	-
High	1	5	4	4	5	1	5	4	1
Moderate	2	10	7	5	13	1	4	9	6
Low	0	8	2	2	8	0	2	6	2
Total	**3**	**23**	**13**	**11**	**26**	**2**	**11**	**19**	**9**

Table reports counts of estimated industry-specific principal component coefficient signs, in total and separately for high/moderate/low industry groupings of the aggregate capital-labour ratio. High/low groups are the top/bottom quartile (ie, ten) industries identified in table 11. Each panel reflects a single regression with the indicated dependent variable. Related industry-specific coefficients on each principal component are reported in the appendix (table A.1). See the associated table note for additional information. The "0" grouping includes coefficients that are insignificantly different from zero at the 10% level.

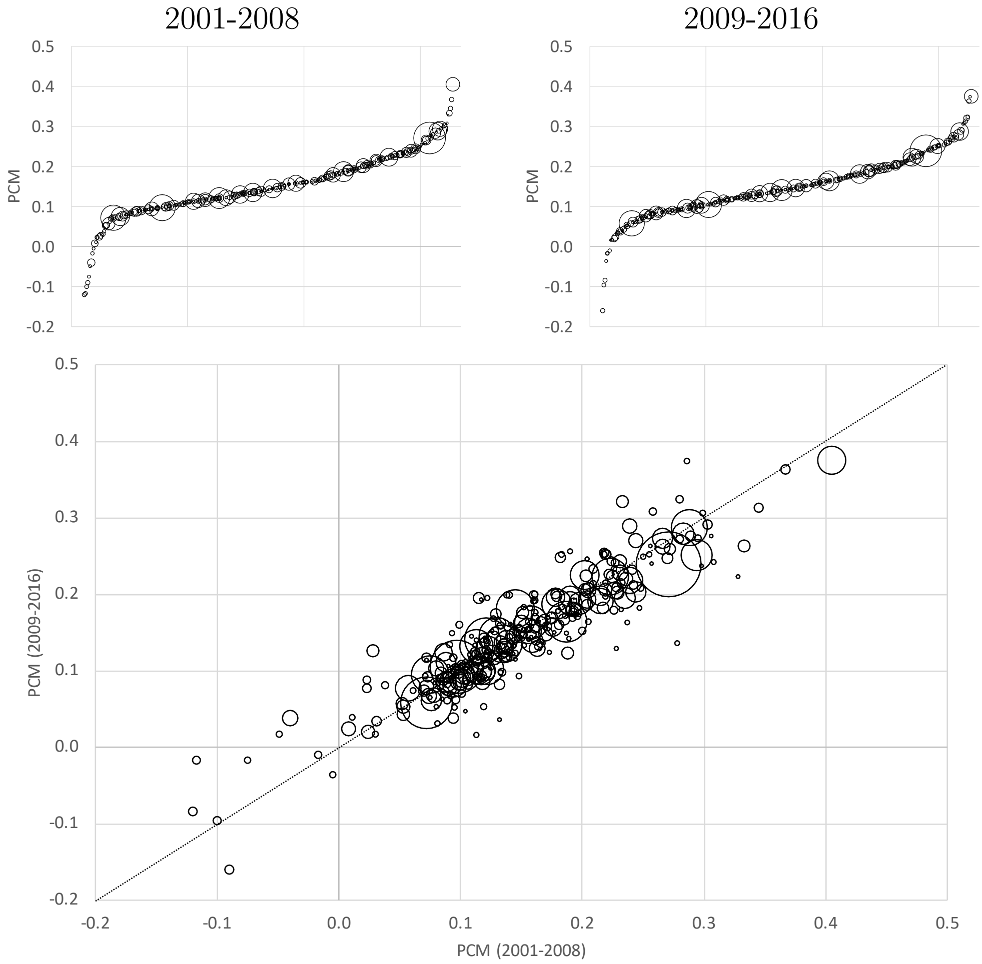
Figures

Figure 1: Profit elasticity by detailed industry and time



Profit elasticities estimated on pooled data with firm fixed effects and time effects, population weighted using firm-level average of productivity population weights. Industry is four-digit ANZSIC, except where industries are grouped at a more aggregate level to ensure at least 200 observations per industry in each time period. Area of bubbles is proportionate to the number of employing firms in the industry. Dashed line in bottom panel indicates constant elasticity across time periods.

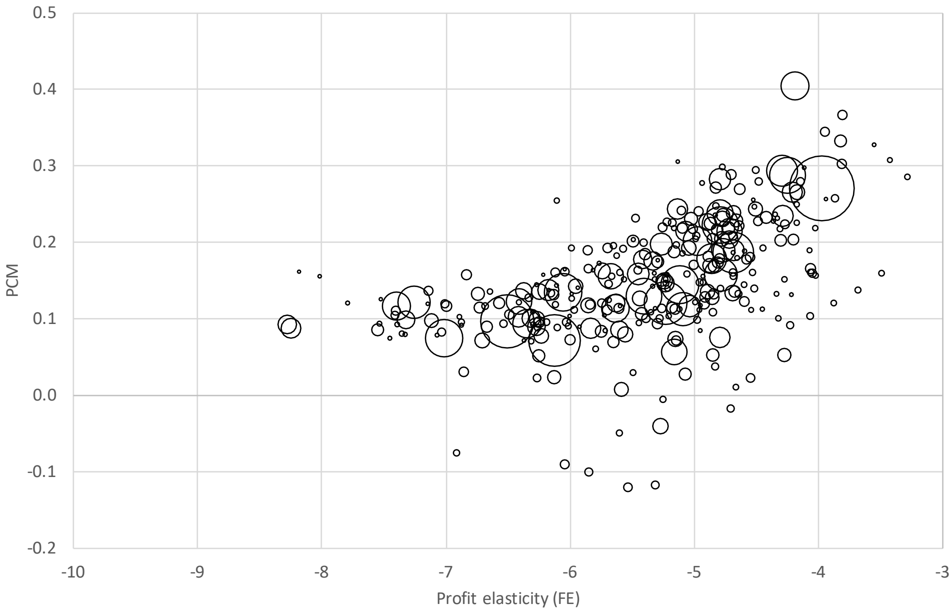
Figure 2: Price-cost margin (PCM) by detailed industry and time



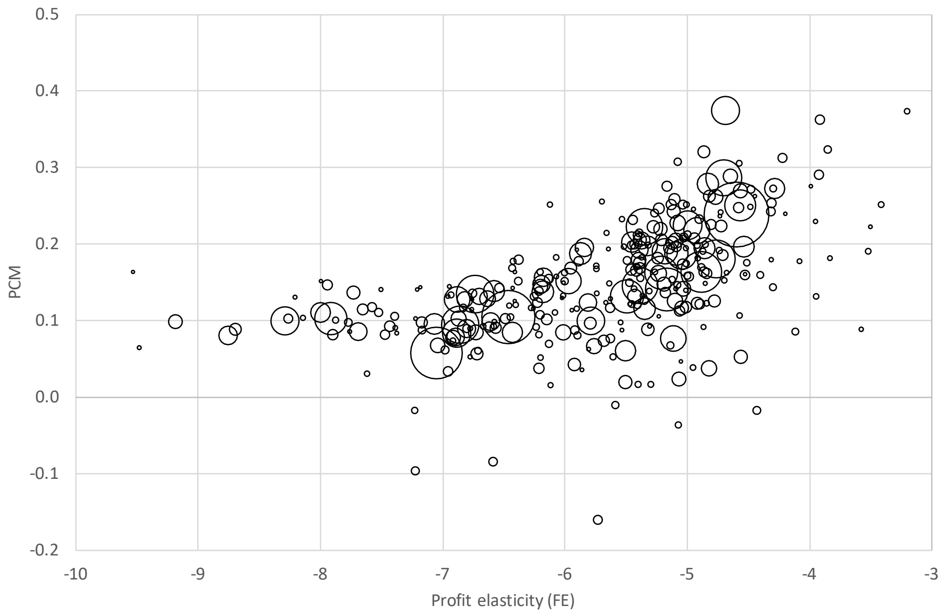
Population-weighted mean of PCM (bounded below at -1). Industry is four-digit ANZSIC, except where industries are grouped at a more aggregate level to ensure at least 200 observations per industry in each time period. Area of bubbles is proportionate to the number of employing firms in the industry. Dashed line in bottom panel indicates constant elasticity across time periods.

Figure 3: Comparison of PE and PCM by detailed industry and time

2001-2008

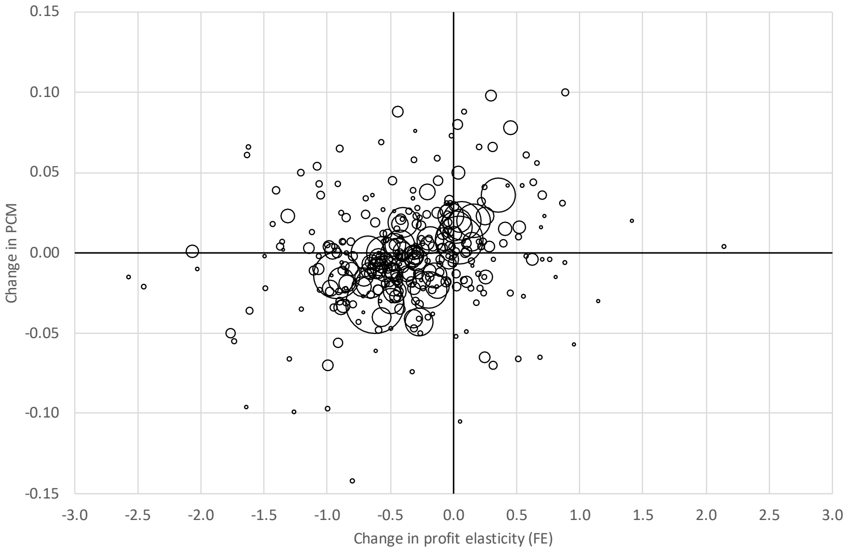


2009-2016



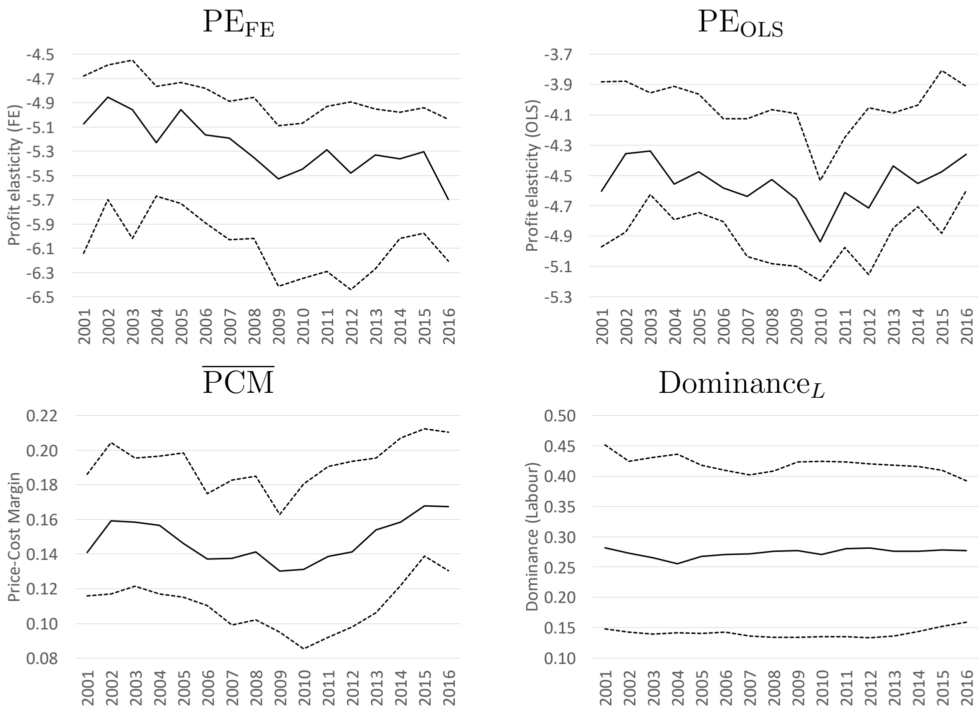
See figures 1 and 2 for notes.

Figure 4: Comparison of change in PE and PCM by detailed industry



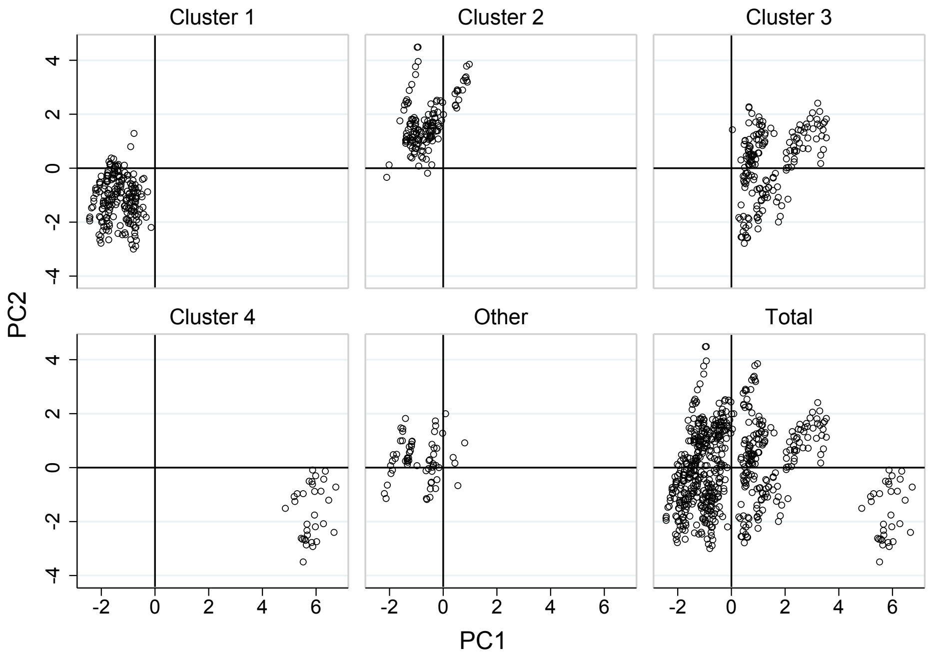
See figures 1 and 2 for notes. Changes measured as the difference between later (2009-2016) and earlier (2001-2008) period values.

Figure 5: Median and interquartile range of industry competition by t – selected metrics



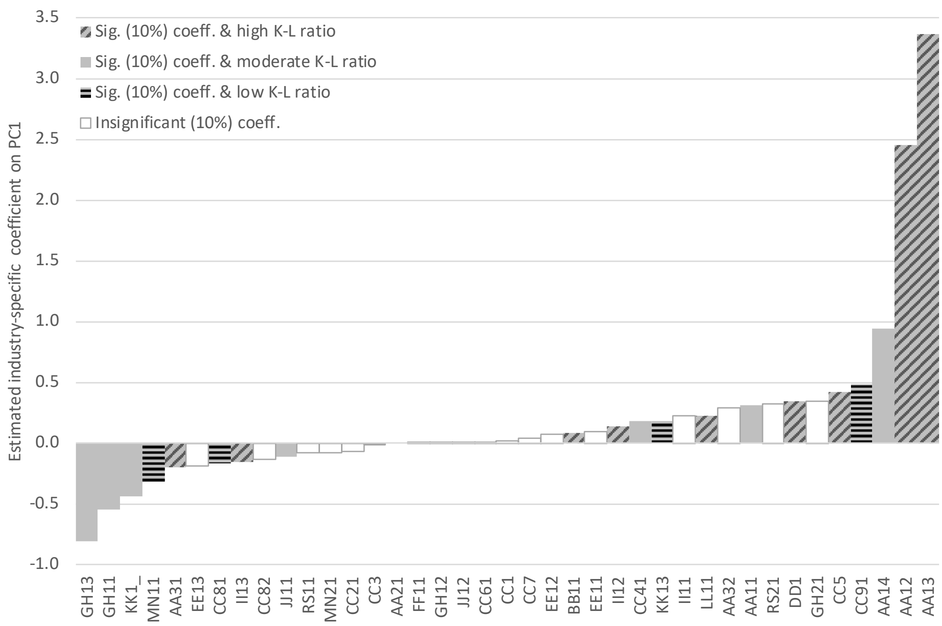
Summary statistics based on 39 productivity industries over 16 years (624 observations). Solid line is median and dashed lines are 25th and 75th percentiles.

Figure 6: Comparison of PC1 and PC2 by industry modal cluster



Industries grouped by PC-based modal cluster. Where the mode does not constitute at least 13 (out of 16) annual observations, the industry is classified to "other" (ie, no predominant cluster). Table 6 reports the productivity industries included in each (modal) cluster.

Figure 7: MFP dispersion and competition – estimated industry-specific PC1 coefficients, grouped by industry capital-labour ratio

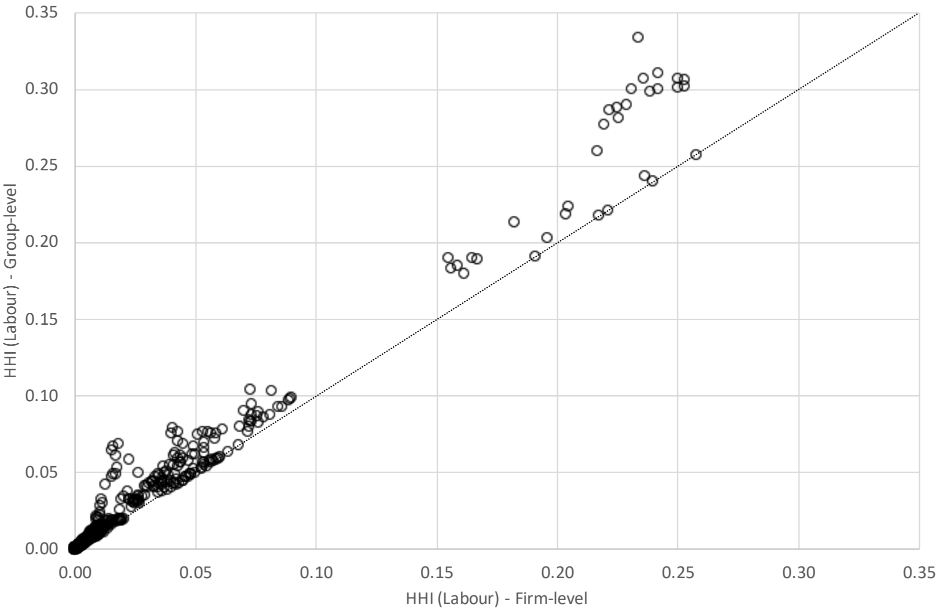


High/low groups are top/bottom quartile of K/L ratio identified in table 11. Coefficients reported in first column of appendix table A.1 (see associated table note for more information). Counts of significant (at 10% level) coefficients match top left quadrant of table 12.

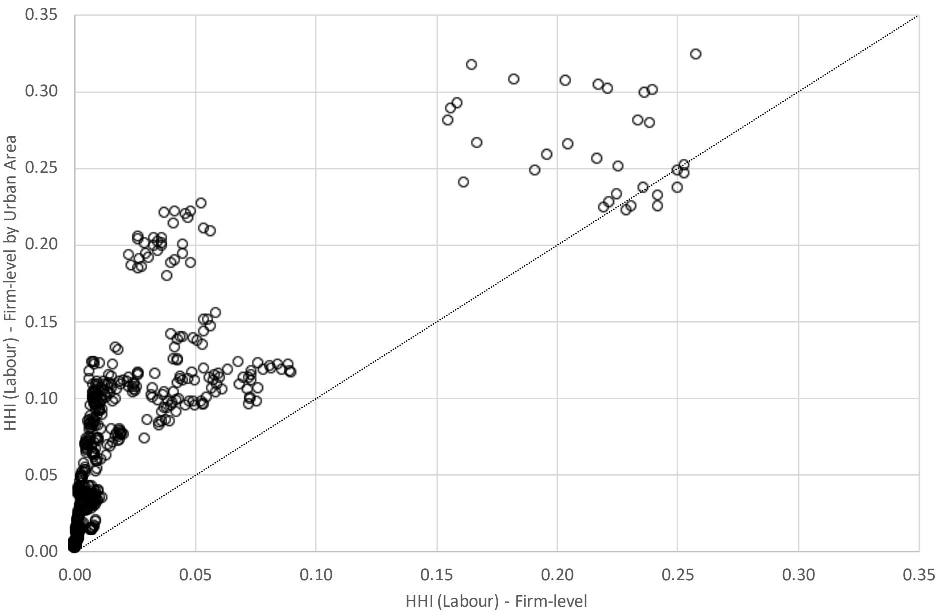
Appendix – Extra results

Figure A.1: Effect of observation level on measured concentration (HHI_L)

Firm- vs group-level



Firm- vs firm by Urban Area-level



Unlike the main analysis, a March year-end financial year is assumed for all firms to enable a consistent aggregation within groups. Grouping of firms is calculated separately for each (March) year to avoid the creation of "mega-groups" resulting from mergers and acquisitions of firms. A grouping algorithm is applied to parent-subsidiary relationships on the Business Register, using data from currently active (employing) enterprises within a permanent enterprise. Firm by Urban Area-level HHI_L aggregated to industry level using UA-level firm count as weight. Dashed line indicates constant HHI across approaches.

Table A.1: Estimated relationship between MFP dispersion, churn and competition – industry-specific coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
		MFP level			MFP dispersion			Firm churn rate			Rel. entry MFP			Rel. exit MFP	
Industry	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
AA11	-0.101	0.108***	-0.045***	0.307**	-0.120***	0.134***	0.030	-0.003	0.008**	0.596***	-0.318***	0.103***	-0.174	-0.028	0.026
	[0.101]	[0.033]	[0.010]	[0.129]	[0.042]	[0.013]	[0.020]	[0.007]	[0.003]	[0.071]	[0.032]	[0.019]	[0.138]	[0.052]	[0.021]
AA12	-0.886***	0.248***	-0.131***	2.453***	-0.719***	0.168***	0.041	0.001	-0.012*	-0.170	0.091	-0.103	-0.060	-0.036	0.111
	[0.280]	[0.079]	[0.020]	[0.377]	[0.109]	[0.034]	[0.048]	[0.014]	[0.006]	[0.323]	[0.107]	[0.065]	[0.392]	[0.119]	[0.068]
AA13	0.322	-0.121*	0.118***	3.366***	-0.935***	0.140***	0.327***	-0.100***	0.028***	0.282	-0.083	0.030	-0.341	0.102	-0.005
	[0.219]	[0.061]	[0.012]	[0.294]	[0.083]	[0.019]	[0.042]	[0.012]	[0.004]	[0.334]	[0.097]	[0.023]	[0.469]	[0.135]	[0.025]
AA14	-0.098	0.041***	0.024***	0.942***	-0.184***	0.042***	0.016	0.008**	0.011***	0.192***	-0.007	0.045**	-0.476***	0.122***	-0.053***
	[0.062]	[0.013]	[0.008]	[0.085]	[0.019]	[0.012]	[0.013]	[0.003]	[0.002]	[0.069]	[0.022]	[0.017]	[0.100]	[0.020]	[0.018]
AA21	-0.008	0.029**	-0.013	0.000	-0.088***	0.095***	0.001	0.004	-0.001	0.020	-0.095***	0.156***	0.092***	0.091***	-0.144***
	[0.018]	[0.013]	[0.009]	[0.020]	[0.016]	[0.011]	[0.003]	[0.003]	[0.003]	[0.017]	[0.010]	[0.010]	[0.032]	[0.013]	[0.017]
AA31	-0.055	-0.023	0.043***	-0.204***	0.106***	-0.041***	0.043***	0.000	0.010***	-0.020	-0.012	0.034***	0.128*	0.052**	0.030***
	[0.033]	[0.016]	[0.005]	[0.039]	[0.019]	[0.005]	[0.007]	[0.003]	[0.002]	[0.034]	[0.008]	[0.007]	[0.066]	[0.021]	[0.008]
AA32	0.005	0.071	0.020**	0.286	-0.132*	-0.008	-0.130***	0.066***	0.005*	0.203	0.087	-0.047**	-1.092***	0.246**	0.076***
	[0.195]	[0.071]	[0.009]	[0.182]	[0.074]	[0.012]	[0.040]	[0.013]	[0.003]	[0.148]	[0.052]	[0.019]	[0.230]	[0.107]	[0.017]
BB11	0.133***	-0.112***	-0.015***	0.085***	-0.096***	-0.008	0.004	-0.057***	0.011***	0.085*	0.016	-0.059***	-0.611***	0.183***	0.189***
	[0.028]	[0.023]	[0.005]	[0.029]	[0.029]	[0.006]	[0.007]	[0.005]	[0.001]	[0.045]	[0.025]	[0.007]	[0.044]	[0.034]	[0.006]
CC1	0.063*	-0.030*	0.021	0.016	-0.008	0.011	0.025**	-0.029**	0.021***	-0.031	0.029	-0.023	-0.272***	0.056	-0.073**
	[0.037]	[0.017]	[0.013]	[0.037]	[0.015]	[0.013]	[0.010]	[0.011]	[0.005]	[0.064]	[0.049]	[0.028]	[0.089]	[0.082]	[0.035]
CC21	0.096	-0.041	-0.007	-0.071	0.037	0.014	0.061***	-0.019**	0.004	-0.114	0.027	-0.029**	-0.491***	-0.098	0.071***
	[0.071]	[0.049]	[0.012]	[0.077]	[0.061]	[0.015]	[0.019]	[0.009]	[0.002]	[0.070]	[0.031]	[0.012]	[0.106]	[0.071]	[0.014]
CC3	-0.009	0.002	0.013**	-0.010	-0.010	-0.003	0.069***	-0.020***	0.008***	0.425***	-0.096***	0.026***	-0.015	0.006	-0.009
	[0.047]	[0.023]	[0.005]	[0.059]	[0.022]	[0.005]	[0.010]	[0.005]	[0.001]	[0.068]	[0.026]	[0.009]	[0.070]	[0.047]	[0.008]
CC41	-0.106*	0.040	0.009*	0.183**	-0.006	-0.014***	0.037***	-0.023***	0.000	0.355***	-0.043**	-0.034***	-0.073	0.034	0.000
	[0.059]	[0.025]	[0.005]	[0.075]	[0.031]	[0.005]	[0.013]	[0.005]	[0.001]	[0.063]	[0.016]	[0.004]	[0.068]	[0.037]	[0.008]
CC5	-0.341**	0.120**	-0.026***	0.416**	-0.202***	0.041***	0.120***	-0.057***	0.016***	-0.216*	0.212***	-0.107***	0.001	0.084	-0.028**
	[0.137]	[0.045]	[0.007]	[0.170]	[0.054]	[0.009]	[0.025]	[0.008]	[0.001]	[0.110]	[0.031]	[0.011]	[0.213]	[0.072]	[0.014]
CC61	0.013	0.010	0.006	0.010	0.062***	-0.038***	-0.026***	0.010***	-0.001	-0.063**	0.036*	-0.005	-0.093**	0.043**	-0.001
	[0.020]	[0.015]	[0.009]	[0.020]	[0.016]	[0.010]	[0.004]	[0.003]	[0.002]	[0.024]	[0.018]	[0.007]	[0.041]	[0.019]	[0.010]

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
		MFP level			MFP dispersion			Firm churn rate			Rel. entry MFP			Rel. exit MFP	
Industry	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
CC7	0.335***	0.001	-0.040***	0.039	0.027	-0.018**	0.055***	-0.015**	0.001	0.041	0.124***	-0.038***	-0.074	0.115**	-0.037***
	[0.052]	[0.020]	[0.008]	[0.072]	[0.022]	[0.008]	[0.011]	[0.006]	[0.002]	[0.056]	[0.032]	[0.011]	[0.062]	[0.046]	[0.011]
CC81	0.098	0.050***	-0.063***	-0.164*	-0.023	0.046***	-0.001	-0.008*	0.000	0.025	-0.043	0.046***	-0.122	0.027	0.050***
	[0.062]	[0.016]	[0.010]	[0.085]	[0.020]	[0.011]	[0.014]	[0.004]	[0.002]	[0.083]	[0.026]	[0.008]	[0.081]	[0.025]	[0.010]
CC82	-0.350***	0.156***	-0.044***	-0.140	-0.019	0.059***	-0.077***	-0.004	0.010***	0.455***	-0.175***	0.044**	-0.225**	0.190***	-0.094***
	[0.098]	[0.035]	[0.014]	[0.091]	[0.032]	[0.016]	[0.023]	[0.008]	[0.003]	[0.092]	[0.053]	[0.018]	[0.102]	[0.055]	[0.030]
CC91	-0.163	0.065	-0.018**	0.480***	-0.082	-0.003	0.013	0.002	-0.004	-0.369***	0.177***	-0.050***	-0.023	0.105*	-0.030*
	[0.124]	[0.042]	[0.008]	[0.152]	[0.051]	[0.011]	[0.029]	[0.009]	[0.002]	[0.129]	[0.031]	[0.015]	[0.163]	[0.053]	[0.017]
DD1	-0.678***	0.119***	0.017**	0.341**	-0.012	-0.015*	0.041*	-0.010**	-0.004**	-0.055	0.128***	-0.001	-0.340***	-0.010	-0.001
	[0.103]	[0.019]	[0.007]	[0.138]	[0.027]	[0.008]	[0.021]	[0.004]	[0.001]	[0.101]	[0.021]	[0.009]	[0.094]	[0.027]	[0.014]
EE11	0.018	0.010	-0.002	0.098	0.045*	-0.045*	-0.052***	0.037***	-0.026***	0.189*	-0.045	0.043*	0.139	-0.033	0.026
	[0.082]	[0.021]	[0.018]	[0.091]	[0.026]	[0.024]	[0.015]	[0.005]	[0.004]	[0.105]	[0.033]	[0.023]	[0.167]	[0.029]	[0.024]
EE12	-0.079	0.045**	-0.026***	0.068	-0.053**	0.034***	0.034***	0.007*	-0.001	-0.244***	-0.097***	0.060***	0.066	0.011	-0.020*
	[0.050]	[0.017]	[0.007]	[0.070]	[0.020]	[0.008]	[0.011]	[0.004]	[0.002]	[0.050]	[0.018]	[0.009]	[0.052]	[0.026]	[0.011]
EE13	-0.382	0.086	-0.002	-0.190	0.054	-0.009	0.004	0.006	0.003	-0.239	0.061	0.048*	0.123	-0.023	0.025
	[0.228]	[0.056]	[0.017]	[0.281]	[0.074]	[0.020]	[0.045]	[0.011]	[0.005]	[0.283]	[0.074]	[0.025]	[0.311]	[0.066]	[0.018]
FF11	0.780***	-0.148*	-0.051***	0.003	-0.008	0.035*	-0.124**	0.027*	0.011**	-0.728*	0.228**	0.004	-0.006	0.050	0.018
	[0.249]	[0.073]	[0.013]	[0.325]	[0.093]	[0.019]	[0.052]	[0.015]	[0.004]	[0.407]	[0.094]	[0.022]	[0.405]	[0.096]	[0.027]
GH11	0.302	-0.013	-0.032***	-0.548**	0.107*	0.038***	-0.123***	0.010	0.001	0.266*	0.022	0.008	0.515	-0.083	-0.020
	[0.219]	[0.043]	[0.010]	[0.265]	[0.053]	[0.012]	[0.042]	[0.008]	[0.003]	[0.145]	[0.028]	[0.019]	[0.334]	[0.051]	[0.026]
GH12	0.005	-0.005	0.037	0.003	0.084**	-0.050	-0.009**	0.022***	-0.001	0.051***	0.148***	-0.010	0.059*	0.077	-0.005
	[0.015]	[0.029]	[0.032]	[0.012]	[0.031]	[0.039]	[0.004]	[0.004]	[0.006]	[0.015]	[0.048]	[0.028]	[0.032]	[0.090]	[0.054]
GH13	1.465***	-0.749***	0.153***	-0.813***	0.568***	-0.185***	0.086***	-0.039***	0.025***	-0.081	0.013	0.097**	0.059	-0.109	0.102**
	[0.112]	[0.066]	[0.027]	[0.140]	[0.083]	[0.030]	[0.029]	[0.014]	[0.008]	[0.171]	[0.051]	[0.047]	[0.170]	[0.091]	[0.044]
GH21	-0.200	0.061	-0.017	0.345	-0.146*	0.101**	-0.036	0.024*	0.004	0.148	0.018	-0.040	0.286	0.001	-0.133
	[0.251]	[0.061]	[0.029]	[0.321]	[0.076]	[0.040]	[0.046]	[0.012]	[0.008]	[0.187]	[0.079]	[0.055]	[0.305]	[0.081]	[0.089]
II11	-0.528***	0.155***	0.004	0.222	-0.023	-0.043**	0.028	-0.006	0.005	0.948***	-0.199*	0.151***	-0.544	0.209	-0.046
	[0.153]	[0.050]	[0.014]	[0.171]	[0.059]	[0.018]	[0.035]	[0.011]	[0.004]	[0.333]	[0.101]	[0.044]	[0.374]	[0.128]	[0.043]

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
		MFP level			MFP dispersion			Firm churn rate			Rel. entry MFP			Rel. exit MFP	
Industry	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
II12	-0.155***	0.123***	-0.018***	0.132***	-0.371***	0.110***	-0.013**	-0.010**	0.007***	0.135***	-0.321***	0.103***	-0.099	-0.389***	0.085***
	[0.021]	[0.017]	[0.004]	[0.029]	[0.016]	[0.003]	[0.006]	[0.004]	[0.001]	[0.035]	[0.035]	[0.009]	[0.074]	[0.041]	[0.008]
II13	0.025	-0.073**	0.018	-0.160**	0.044	0.005	-0.061***	0.016**	0.015***	0.090	-0.107*	0.026*	-0.022	-0.079	0.040**
	[0.051]	[0.028]	[0.013]	[0.067]	[0.028]	[0.015]	[0.011]	[0.007]	[0.004]	[0.074]	[0.054]	[0.015]	[0.069]	[0.073]	[0.019]
JJ11	0.067*	-0.016	0.036***	-0.117**	-0.015	-0.013	0.021***	-0.002	-0.002	-0.087***	-0.097***	0.010	-0.162***	-0.179***	0.098***
	[0.034]	[0.018]	[0.005]	[0.045]	[0.020]	[0.008]	[0.008]	[0.004]	[0.002]	[0.027]	[0.025]	[0.023]	[0.035]	[0.030]	[0.020]
JJ12	-0.131***	-0.152***	0.045***	0.005	0.027	-0.052***	0.035***	-0.007*	-0.008***	0.002	0.073***	0.017**	-0.135***	0.168***	0.064***
	[0.013]	[0.018]	[0.008]	[0.017]	[0.022]	[0.009]	[0.003]	[0.004]	[0.002]	[0.018]	[0.020]	[0.007]	[0.018]	[0.027]	[0.012]
KK13	-0.284***	0.143***	0.024***	0.183*	-0.096***	0.016*	-0.024	-0.001	-0.004	-0.527***	0.191***	-0.098***	0.000	0.011	-0.023
	[0.077]	[0.027]	[0.008]	[0.092]	[0.032]	[0.008]	[0.017]	[0.006]	[0.002]	[0.082]	[0.032]	[0.025]	[0.098]	[0.054]	[0.018]
KK1_	-0.041	0.127***	-0.034***	-0.438***	0.044***	0.022**	0.063***	-0.023***	-0.002	-0.757***	-0.066***	0.112***	-0.265***	-0.011	0.034**
	[0.072]	[0.010]	[0.008]	[0.087]	[0.012]	[0.009]	[0.012]	[0.003]	[0.002]	[0.045]	[0.015]	[0.012]	[0.096]	[0.023]	[0.013]
LL11	-0.298***	-0.014	0.068***	0.223***	0.027	-0.062***	0.108***	0.002	0.002	-0.226***	0.145***	0.065***	-0.583***	0.135***	0.059
	[0.068]	[0.020]	[0.017]	[0.074]	[0.021]	[0.019]	[0.017]	[0.005]	[0.003]	[0.063]	[0.028]	[0.016]	[0.080]	[0.039]	[0.037]
MN11	-0.279*	0.117**	-0.032	-0.315*	0.010	0.032	-0.016	0.004	0.041***	-0.374**	0.120*	0.043	0.073	-0.019	0.069
	[0.163]	[0.047]	[0.030]	[0.183]	[0.052]	[0.041]	[0.032]	[0.013]	[0.008]	[0.154]	[0.070]	[0.054]	[0.215]	[0.064]	[0.046]
MN21	-0.023	0.077*	-0.005	-0.077	0.028	-0.061**	-0.004	0.011	-0.003	0.128	0.031	0.010	0.008	-0.018	-0.004
	[0.060]	[0.044]	[0.026]	[0.064]	[0.044]	[0.028]	[0.014]	[0.011]	[0.006]	[0.084]	[0.037]	[0.033]	[0.063]	[0.052]	[0.027]
RS11	0.004	0.021	-0.001	-0.083	0.021	0.005	-0.022**	0.007	-0.006*	-0.001	0.007	-0.023*	-0.226***	0.044	-0.058***
	[0.043]	[0.022]	[0.013]	[0.054]	[0.027]	[0.014]	[0.009]	[0.005]	[0.003]	[0.041]	[0.020]	[0.013]	[0.075]	[0.028]	[0.020]
RS21	-0.073	0.091	-0.080	0.322	-0.066	0.094	0.016	-0.023	0.039***	0.131	-0.003	0.029	-0.583	0.139	0.070
	[0.207]	[0.096]	[0.064]	[0.248]	[0.117]	[0.085]	[0.054]	[0.021]	[0.014]	[0.268]	[0.085]	[0.066]	[0.379]	[0.147]	[0.072]
N(observations)		624			624			585			507			507	
Adjusted R^2		0.741			0.987			0.942			0.571			0.449	

Each set of three principal component coefficients constitutes a single regression (including year and industry dummies) where the independent variable is noted at the top of the table. MFP level includes an industry time trend component. MFP and MFP dispersion coefficients estimated on dataset with 39 productivity industries over 16 years (624 observations). Churn rate regression exclude the 2016 year, since it is not possible to consistently identify firm exit in 2017 with the available data. For relative MFP entry/exit, we lose a further year of data because of the use of adjacent year MFP. MFP is relative to incumbent firms, and single-year firms (entrant-exiters) are excluded. Robust standard errors (clustered on industry) reported in brackets. Stars indicate coefficients are significantly different from zero at the 1% (***), 5% (**) or 10% (*) level. Industry descriptors are included in table 6.

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