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# Uncovering the Urban Advantage of Australian Firms: New Evidence from BLADE Data

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This paper quantifies the productivity advantages of urban firms within and across Australian states and industries. Following Combes et al. (2012), we decompose the source of urban advantages into agglomeration and selection effects using the most exhaustive data source on Australian businesses: BLADE. Our findings show that most of the urban productivity advantages are due to agglomeration effects and that these advantages differ substantially across Australian states. They range from 10% in WA to 1.5% in SA in terms of relative urban productivity gains for a representative firm with mean productivity. These advantages also vary across industries: they are twice as large for manufacturing firms in QLD (5.1%) vs NSW (2.4%) while nearly three times as large for service firms in NSW (11.7%) vs QLD (4.1%). Urban advantages are concentrated among mature firms, and among high-productivity businesses within young firms.

**Keywords**

Agglomeration; Productivity Advantages; Regional vs Urban; Selection; Firms

**JEL Classification**

D24; E24; H77; O4; C81; R3; R5

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# Uncovering the Urban Advantage of Australian Firms: New Evidence from BLADE Data*

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# 1 Introduction

Regional development policies have attracted significant attention among academics and policymakers over the years. These initiatives are particularly relevant for Australia, which, according to the World Bank, ranks 30th for urbanisation while 226th for population density worldwide.[1] That is, Australia's non-urban areas (from inner regional to very remote) typically represent a low share of the total population, and are characterised by exceptionally low population density.

Given this peculiar geographical and urban configuration, one key objective of regional development policies in Australia has been to increase employment opportunities in rural areas. As such, the relocation of businesses has formed the backbone of many proposals, as illustrated in a recent quote from the House of Representatives Select Committee on Regional Australia (2022):[2]

> *"The Committee recommends that the Australian Government implement a program for promoting the advantages of locating businesses in regional areas (...) and look at ways to incentivise business into regional areas."*

While there are many advantages of promoting a more industrialised rural economy, such policies face a key obstacle: "the urban advantage." That is, firms are, on average, more productive in cities.[3] In turn, policies that incentivise the relocation of firms from major cities to rural areas need to consider not only the *size*, but also the *source* of the urban advantage to avoid potentially large productivity losses.

This paper quantifies the productivity advantages of urban firms within and across Australian states and industries. These advantages are typically assumed to originate in *agglomeration* economies that arise as a result of Marshallian externalities. But such urban advantages might be also shaped by firm *selection*: larger cities tend to enhance the competitiveness of an industry and facilitate the entry of more productive firms, as well as the exit of the least productive ones. Following the methodology of Combes et al. (2012), this paper decomposes the source of urban advantages into agglomeration and selection effects. Such distinction is relevant for policymaking. If agglomeration effects are the sole drivers of the urban advantage, their quantification would provide a measure

[1] An example of a government initiative is Regional Development Australia (RDA), which is a national network of local leaders to support the economic development of regional Australia. The establishment and challenges of the RDA are discussed in Buultjens et al. (2016).

[2] See House of Representatives (2022).

[3] See, for example, Rosenthal and Strange (2004).

of the opportunity cost (in terms of productivity losses) from incentivising firms to locate in non-urban regions. If selection effects are important, firms that do not survive in the urban environment could potentially be viable in the rural space, which could dampen the productivity losses from shifting production to non-urban areas.

To quantify these effects, we use the most exhaustive data set currently available on Australian businesses: the Business Longitudinal Analysis Data Environment (BLADE). Our findings show that most of the urban productivity advantages are due to agglomeration effects and that these advantages differ substantially across Australian states. It ranges from 10% in WA to 1.5 % in SA in terms of relative urban productivity gains for a representative firm of mean productivity. These advantages also vary across industries. Urban advantages are twice as large for manufacturing firms in QLD (5.1%) vs NSW (2.4%), while nearly three times as large for service firms in NSW (11.7%) vs QLD (4.1%).

Additionally, we find that urban advantages are concentrated among mature firms (older than 3 years). Within young businesses, high-productivity firms may be benefiting the most from being located in an urban environment. Relatedly, high-productivity service firms seem to enjoy larger urban gains than manufacturing firms of high-productivity.

**Related Literature.** The literature on the productivity advantages of cities is divided into exploring two main mechanisms: agglomeration economies and firm selection.

Following Marshall (1898), agglomeration economies convey that, regardless of the underlying firm productivity, cities provide productivity-enhancing externalities.[4] These externalities may come from input sharing, labour pooling and/or knowledge spillovers.[5] Abdel Rahman and Fujita (1990) argue that there are productivity benefits from allowing intermediate producers to specialise. Such specialisation is empirically supported by Ellison and Glaeser (1997), who find evidence of geographical clustering across manufacturing industries in the U.S.. The notion that cities can facilitate workforce specialisation is formally established by Kim (1989) by building a model where workers can invest into either "specialised" human capital or the "breadth" of their human capital. This labour pooling mechanism is illustrated in the location choices of "power couples" in the U.S. as shown in Costa and Kahn (2000), and through the degree of resource mis-allocation in French employment areas in Fontagne and Santoni (2019). Knowledge spillovers have

[4] Bradley and Gans (2007) study the determinants of the growth of Australian cities to understand the Australian economy-wide growth. Recently, and also for Australia, Leishman and Liang (2022) estimate that 1% increase in the population of cities leads to average productivity increases of 0.24 - 1.70 %.

[5] Duranton and Puga (2004) provide a review of the existing theoretical models, while Rosenthal and Strange (2004) review the empirical evidence on agglomeration economies.

been are micro-founded in the endogenous growth literature by the seminal works of Romer (1986) (through learning-by-doing via the external effects of capital accumulation), and Lucas (1988) (through individual investment into human capital via internal and external impacts on worker productivity). Empirical evidence of knowledge spillovers has been documented by Glaeser et al. (1992), who study employment concentration of large U.S. industries in 170 cities between 1956 and 1987. For Australia, Darchen (2012) finds evidence of knowledge spillovers in the videogame industry in Brisbane and Melbourne. However, the literature acknowledges the difficulties of isolating a causal effect between urban clustering and knowledge spillovers.

The firm selection mechanism was introduced by Porter (1990), which formalises the phenomenon that larger markets attract the entry of more productive firms and facilitate the exit of unproductive businesses. The theoretical foundations of firm selection have been established by the influential works of Hopenhayn (1992) and Melitz (2003). Building on these frameworks, Nocke (2006) endogenises market selection as the outcome of an anonymous game among firms. Such game leads to higher (lower) productivity firms to select into larger (smaller) markets. Syverson (2004) studied these selection effects in a spatially differentiated product market model and evidenced for the ready-made concrete sector in the U.S..

In the last decade, there have been a number of papers that nest both agglomeration economies and firm selection effects. A key contribution is Combes et al. (2012), which is the building block of this paper. Arimoto et al. (2014) also employs this model to study agglomeration and selection in the silk reeling firms in Japan from 1908 to 1915. However, the magnitudes of both effects are impacted by the ordering of firms into urban and non-urban, as shown by Accetturo et al. (2018), which applies the same methodology to a panel data of Italian manufacturing firms.

These urban productivity advantages have been found to affect the wage premia, as shown by Glaeser and Mare (2001), Combes et al. (2008) and De La Roca and Puga (2017), among others. The urban wage premium in Australia suggests wages rise 1.6% with a doubling in population density as shown by Meekes (2022). However, Vij et al. (2021) argue that urban wage premia are insufficient to mitigate congestion costs which may continue to increase over time under current policy settings in Australia. Furthermore, wage premia also lead to the "nursery city" idea of diversified and specialised cities, that facilitate innovation and production, as in Duranton and Puga (2001) and Faggio et al. (2017). Evidence of specialisation of Australian cities has been found by Beer and Clower

(2009).

**Layout of the paper.** The layout of the remainder of the paper is as follows. Section 2 provides an overview of the model and estimation approach. Section 3 describes the data. Section 4 presents the results. Section 5 concludes.

# 2 Model and Estimation Approach

In this section we provide a simplified description of the model in Combes et al. (2012), and present the estimation approach developed in that paper. When describing the model, we only focus on the key relationships which will be needed for the estimation. Accordingly, we deliberately omit some of the microfoundations on which the model builds, and refer the reader to the original paper for details.

## 2.1 Model

Consider and economy composed of $I$ cities (or locations) indexed by $i = \{1, ..., I\}$, which differ across population sizes.[6] A representative consumer derives utility from differentiated goods (or varieties), which are produced under monopolistic competition by a continuum of firms located across cities. Firms are immobile and markets for differentiated goods are segmented, in the sense that firms incur trade costs when selling goods outside the city they are located.

To produce a variety, firms must incur a sunk entry cost and hire labor, which is the only input in production.[7] Let $h$ denote the units of labor required to produce one unit of output, and assume that units are chosen so that $h$ is also the marginal cost faced by a firm. Importantly, firms are heterogeneous across $h$, and draw this input requirement from the cumulative distribution function $G(h)$ after paying for the entry cost. The distribution $G(h)$ is common across cities.

It is assumed that consumer preferences are symmetric in product varieties. Accordingly, firms can be uniquely identified by $(i, h)$, i.e., by the city in which they are located, and by their marginal cost. We refer to the level of *productivity* of a firm as the level of

[6] For our purposes, the source of heterogeneity across cities can be generalised. Our estimation approach essentially requires that the distribution of firm productivity in urban cities differs from the one in non-urban cities.

[7] Results can be extended to the case of multiple inputs.

output per worker produced by such a firm in equilibrium. In turn, we define $\phi_i(h)$ as the natural logarithm of firm's $(i, h)$ productivity. For the rest of the analysis, we make the following assumption regarding the functional form of $\phi_i(h)$:

**Assumption 1.** *The natural logarithm of firm's $(i, h)$ productivity satisfies*

$$\phi_i(h) = A_i - D_i \ln(h). \tag{1}$$

The parameters $A_i$ and $D_i$ encapsulate the forces of *agglomeration* in city $i$. To be precise, for $A_i \geq 0$ and $D_i \geq 1$, stronger agglomeration effects are reflected in larger values of *both* of these parameters. Intuitively, if agglomeration forces become stronger, all firms in city $i$ become more productive (due to a larger $A_i$), but more productive firms benefit relatively more (due to a larger $D_i$ above unity).

Given to the presence of entry costs, there exists a marginal cost threshold $\bar{h}_i$ such that only firms with $h \leq \bar{h}_i$ sell in the market of city $i$. This threshold is pinned down by a free entry condition, which makes ex-ante expected profits equal to zero in equilibrium. Firms in city $i$ with $h > \bar{h}_i$ cannot cover marginal costs and exit the market. Accordingly, let

$$S_i \equiv 1 - G(\bar{h}_i) \tag{2}$$

denote the share of firms that fail to survive in city $i$. The coefficient $S_i$ is a measure of the strength of *selection*—or of the toughness of competition—in city $i$.

Based on (1) and (2), it is straightforward to show that the cumulative density function of log productivity for active firms in city $i$ is given by

$$F_i(\phi) = \max\left\{0, \frac{\tilde{F}\left(\frac{\phi - A_i}{D_i}\right) - S_i}{1 - S_i}\right\}, \tag{3}$$

where $\tilde{F}$ is the underlying productivity distribution of log productivity in the absence of agglomeration and selection effects, i.e., when $A_i = 0$, $D_i = 1$, and $S_i = 0$.

Notably, stronger agglomeration effects right-shift and dilate the benchmark distribution $\tilde{F}$. Stronger selection, on the other hand, left-truncates the distribution of log productivity. These properties will be exploited in the next subsection to identify the forces of agglomeration and selection in urban relative to non-urban areas.

## 2.2 Estimation Approach

Since $\tilde{F}$ is unobservable, we cannot directly estimate the parameters $A_i$, $D_i$ and $S_i$ for each city $i$ based on equation (3). Nevertheless, under mild conditions, one can still identify the *relative* strengths of agglomeration and selection across different cities. Specifically, suppose that (3) holds for all $i$, and that $\tilde{F}$ is invertible. Take two different cities indexed by $i = \{\mathcal{U}, \mathcal{R}\}$, let $\lambda_i(q) \equiv F_i^{-1}(q)$ denote the $q$th quantile of $F_i$, and let

$$A \equiv A_{\mathcal{U}} - DA_{\mathcal{R}}, \quad D \equiv \frac{D_{\mathcal{U}}}{D_{\mathcal{R}}}, \quad S \equiv \frac{S_{\mathcal{U}} - S_{\mathcal{R}}}{1 - S_{\mathcal{R}}}, \tag{4}$$

denote, respectively, the relative shift, dilation and truncation parameters between locations $\mathcal{U}$ and $\mathcal{R}$. Then, as shown by Combes et al. (2012), the quantiles of the log productivity distributions in cities $\mathcal{U}$ and $\mathcal{R}$ are related by

$$\lambda_{\mathcal{U}}(q) = D\lambda_{\mathcal{R}}\left(S + (1-S)q\right) + A, \quad \text{for} \quad q \in \left[\max\left\{0, \frac{-S}{1-S}\right\}, 1\right]. \tag{5}$$

In a nutshell, equation (5) establishes a link between the quantiles of the productivity distributions of two different locations. Importantly, such a relationship is shaped by the relative parameters defined in (4), and does not depend on the quantiles of the unobservable distribution $\tilde{F}$. The cities $i = \mathcal{U}$ and $i = \mathcal{R}$ will later be mapped to urban and non-urban locations, respectively, in the data.[8]

The domain restriction in (5) (which accounts for the fact that $S$ can be negative) poses an issue for estimation, since $S$ is unobservable. This problem can be overcome by applying a change of variables, leading to the main estimation equation:

$$\lambda_{\mathcal{U}}(\rho_S(q)) = D\lambda_{\mathcal{R}}\left(S + (1-S)\rho_S(q)\right) + A, \quad \text{for} \quad q \in [0,1], \tag{6}$$

where $\rho_S(q) \equiv \max\left\{0, \frac{-S}{1-S}\right\} + \left(1 - \max\left\{0, \frac{-S}{1-S}\right\}\right) q$.

Our goal below is to estimate $(A, D, S)$ when comparing urban vs non-urban firms, based on equation (6). The estimation approach aims to minimise the mean squared error of (6), *and* of the reverse comparison between the quantiles of the distributions $F_{\mathcal{R}}$ and $F_{\mathcal{U}}$.[9] Further details are provided in Appendix A.

[8] A precise definition of urban and non-urban firms is presented in Section 3.

[9] Such "reverse comparison" is obtained by writing a version of equation (6) involving the quantiles of the log productivity distribution of location $\mathcal{R}$ and the quantiles of a modified distribution of log productivity in $\mathcal{U}$. By incorporating this comparison in the estimation, the method avoids treating the productivity

We should highlight that our estimation approach does not impose any constraints on the range of $(A, D, S)$. Therefore, we do allow for estimates reflecting either negative agglomeration (in the form of $A < 0$ and/or $D < 1$), or relatively more selection in non-urban areas (which occurs when $S < 0$).

### 2.2.1 Estimation of Firm-Level TFP

We conclude this section by discussing our approach to estimate firm total factor productivity (TFP). While the model presented above only involves one input, equation (6) would still hold in the case of multiple inputs (after reinterpreting the parameters $(A, D, S)$ accordingly). In turn, for our estimation of TFP we generalise the production function of the firm to allow for capital and intermediate inputs.

Specifically, in our benchmark calibration we assume that firms operate a Cobb-Douglas production function, so that firm-level TFP can be measured based on the residuals of the linear regression

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \phi_{it}, \tag{7}$$

where $y_{it}$, $l_{it}$, $k_{it}$, $m_{it}$, $\phi_{it}$ are, respectively, the natural logs of gross output, full-time employees, capital, intermediate input purchases and total factor productivity of firm $i$ in year $t$.

The above equation is estimated using ordinary least squares. Our measure of firm-specific TFP, $\hat{\phi}_i$, is then computed as

$$\hat{\phi}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} \hat{\phi}_{it},$$

where $\hat{\phi}_{it}$ corresponds to the residuals of (7), and $T_i$ is the number of years that firm $i$ is observed.[10]

distributions of $\mathcal{U}$ and $\mathcal{R}$ asymmetrically.

[10]Ideally, one would differentiate between high-and low-skilled labour. However, our main dataset (BLADE) does not contain occupation level data for each firm, nor is there a complete history of occupational data available for linkage with our data. Other works using BLADE have overcome this limitation by segmenting the estimation (and subsequent analysis) into industries, under the assumption that labour skill shares are relatively homogeneous among industry categories (see La Cava and Hambur (2018)). For the purposes of this analysis, we will be estimating models at the two-digit ANZSIC level and/or by sector (manufacturing and services), which will control for some heterogeneity in input elasticities, labour and capital across industries whilst still allowing a sufficiently large sample in each estimation step.

# 3 Data

Our main data source is the Business Longitudinal Analysis Data Environment (BLADE); a collection of data sets containing the most exhaustive micro-level data on Australian firms.[11] BLADE is constructed by the Australian Bureau of Statistics (ABS) by integrating information from a number of sources, including business surveys as well as government administrative tax data. The various data sets in BLADE are linked through anonymised Australian Business Numbers (ABNs), and comprise all active businesses with annual revenue over $75,000 in Australia. At the time we started this empirical analysis, the longitudinal annual data in BLADE ranged between fiscal years 2001-02 and 2018-19.

**Unit of Observation.** The unit of observation in BLADE (i.e., what we refer to as a "firm" or a "business") is a Type of Activity Unit (TAU). Each TAU is a producing unit which can report a minimum set of productive and employment data, namely: total capital expenditure, income from the sale of goods and services, wages and salaries, total inventories, total purchases, and selected expenses.

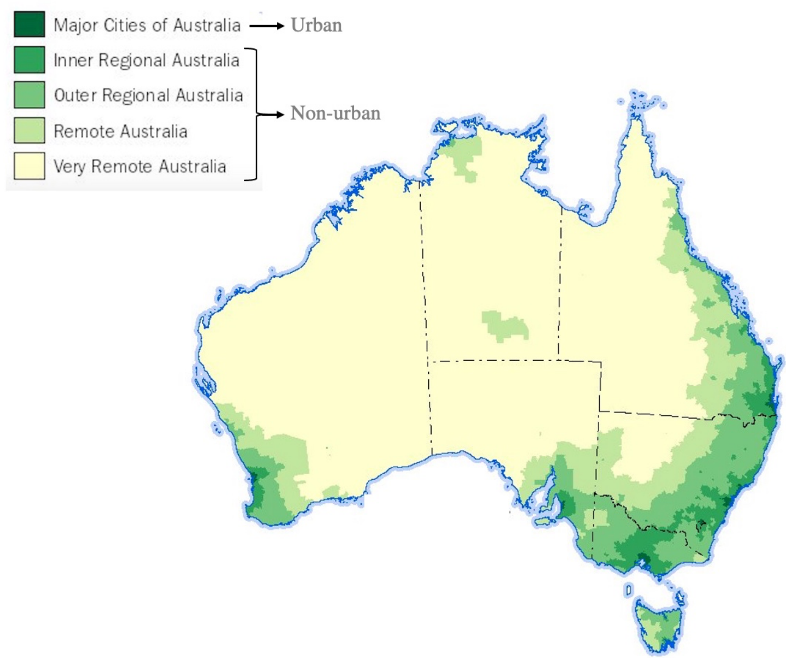
We should highlight that for the vast majority of businesses in BLADE, the relationship between a TAU and an ABN is one-to-one. This is what the ABS refers to as the "non-profiled" population. However, for firms with complex legal structures—the "profiled" population—a TAU may correspond to several ABNs or vice-versa (a typical example is an enterprise group with many operations across different industry subdivisions).[12]

**Urban Classification.** We classify firms as "urban" or "non-urban" based on firms' postcodes, and in terms of distance from service centres. The first step is to locate firms in our sample across Remoteness Areas, which is a classification followed by the Australian Statistical Geography Standard (ASGS). Under this classification, Satistiscal Areas Level 1 (SA1s) are assigned a degree of remoteness based on relative access to services (health, education, etc.) on a five point scale: Major Cities, Inner Regional, Outer Regional, Remote, and Very Remote. Next, we categorise firms as "urban" if their postcode belongs to a Major City. All other firms are classified as "non-urban." Figure 1 plots the Remoteness

[11]See Parker (2017), Hansell and Rafi (2018) and McMillan and Burns (2021) for overviews of BLADE. Recent works using BLADE and earlier versions of this data environment include Bakhtiari (2019), Breunig et al. (2020) and La Cava and Hambur (2018), among others.

[12]While not included in this version of the paper, the results are robust to considering only non-profiled firms.

**Figure 1:** Remoteness Area Boundaries (2016) and Urban Classification.




*Source: ABS Catalogue No. 1270.0.55.005, 1270.0.55.001.*

Areas for Australia in 2016, and shows its mapping with the urban classification of firms applied in this paper.

It should be noted that the above classification differs from the one applied by Combes et al. (2012), which is based on population density. Our baseline principle to stratify our sample into urban and non-urban is in line with the work Accetturo et al. (2018), who apply a notion of "market access." These authors highlight that trade costs may be asymmetric between locations and this, in turn, can cause the intensity of selection to be heterogeneous among areas of the same population density.

**Sample Selection.** We focus on the "core" section of BLADE, which primarily comprises administrative data from the Australian Taxation Office (ATO) sourced from Business Activity Statements (BAS), Business Income Tax Returns (BIT), and Pay as You Go Statements (PAYG).[13] Our sample spans fiscal years 2010-11 through 2017-18. We use data post 2009 to bypass the impact of the Great Financial Crisis, and truncate the sample in

[13] This data is a byproduct of an administrative process whereby firms remit Gross Service Tax, and fulfill their income and payroll tax obligations.

2017-19 due to the lack of data for some components of the BLADE core in 2018-19.[14]

The following types of firms were excluded from our sample: legal structures which are not required to submit BIT statements, firms with incomplete BIT returns, public sector and not-for-profit organisations, firms with missing industry codes or whose industry code did not match their division, and firms which were no longer trading at the beginning of the period of interest or had no revenue.

**Table 1:** Firm-year Observations by State, Urban Classification, and Sector.

| | NSW | VIC | QLD | SA | WA | Total |
|---|---|---|---|---|---|---|
| **By Urban Classification** | | | | | | |
| Urban | 327,560 | 269,814 | 167,974 | 53,230 | 103,994 | 922,572 |
| Non-Urban | 60,654 | 50,470 | 56,417 | 15,015 | 17,638 | 200,194 |
| **By Sector** | | | | | | |
| Services | 279,911 | 215,770 | 153,421 | 40,524 | 82,362 | 771,988 |
| Manufacturing | 108,303 | 104,514 | 70,970 | 27,721 | 39,270 | 350,778 |
| **Total** | 388,214 | 320,284 | 224,391 | 68,245 | 121,632 | 1,122,766 |

In addition, we only include firms which fall within manufacturing or services related industries, which is consistent with the empirical analysis of Combes et al. (2012) and Accetturo et al. (2018). One important reason for excluding other industries is the lack of sufficient variation between urban and non-urban areas (e.g., for mining and agriculture the majority of economic activity occurs outside urban areas).

For our state-level analysis, we concentrate on the five largest Australian states, i.e., New South Wales (NSW), Victoria (VIC), Queensland (QLD), South Australia (SA), and Western Australia (WA). We exclude Tasmania (TAS), and the internal territories as their samples sizes are relatively small.

[14] At the time of writing, BIT data for 2018-19 was still under the process of being finalised.

Our sample comprises 1,122,766 firm-year observations in total. Table 1 breaks down this count by state, urban classification, and sector.

**Estimating Firm-Level TFP.** To estimate idiosyncratic productivity via (7), we use firm-level measures of labour, capital, intermediate inputs, and output reported in BLADE. Our measure of labour corresponds to full-time equivalent employees.[15] To proxy capital, we use non-current assets (which include land, buildings, machinery, etc.) reported at depreciated cost for tax accounting purposes. This approach is consistent with La Cava and Hambur (2018), for example, who also use BLADE to estimate firm-level productivity.[16] Intermediate purchases and output are measured using turnover and operating expenses, respectively. Both of these variables are reported on firms' BAS.

One key conceptual limitation of BLADE is the absence of a quantity measure of output, capital, and intermediate goods. To control for changes in prices, these variables are deflated by the ABS Producer Price Indices, containing price information across industries. This method has been applied in similar productivity estimation exercises based on BLADE data, such as Andrews and Riedl (2019). Whilst this is a practical way of controlling for variations in prices across time and industry codes, it does not consider within-industry variation of prices. As a mitigating factor, we perform productivity estimation at the two-digit ANZSIC level.

# 4 Results

This section presents the empirical findings of the paper. We split the discussion into two parts. In Subsection 4.1 we discuss the results at the country-level: we quantify and decompose the Australia-wide urban advantage, and study how it varies across industries and firm ages. Next, in Subsection 4.2, we further disaggregate the analysis by looking at state-level variations.

[15]Using full-time equivalent employees does not come without a cost, since PAYG employment figures are not necessarily put forward by every firm that submits a BAS. This results in a sizeable amount of missing data (mostly from sole proprietors who are not required to submit PAYG summaries). Fox (2019) posits that a sensible method of dealing with firms with zero or missing employees and wage data is to replace the missing employee data with one to represent sole proprietorship.

[16]BLADE posits at least two key limitations for estimating capital inputs via the widespread perpetual inventory method. First, there is often insufficient data on capital expenditure for smaller firms (with less than $10m in annual turnover) to get reliable estimates. Second, data available on heterogeneous depreciation rates across asset types is insufficiently granular for the perpetual inventory method to improve upon the quality of our estimates.

**Table 2:** Country-Level Estimates.

| Sector | Urban Advantage | $\hat{A}$ | $\hat{D}$ | $\hat{S}$ | $R^2$ |
|---|---|---|---|---|---|
| All Sectors | 6.8% | 0.0654 | 1.1057 | 0.0019 | 0.94 |
| | | (0.0017)*** | ( 0.0049)*** | (0.0003)*** | |
| Services | 8.7% | 0.0831 | 1.0766 | 0.0013 | 0.95 |
| | | (0.0024)*** | (0.0046)*** | (0.0003)*** | |
| Manufacturing | 3.9% | 0.0381 | 0.9630 | -0.0011 | 0.80 |
| | | (0.0025)*** | (0.0066)*** | (0.0004)*** | |

Bootstrapped standard errors are reported in parentheses. ***, **, and * indicate significance above 1%, 5%, and 10%, respectively, under the null hypothesis of $A = 0$, $D = 1$ or $S = 0$, depending on the column.

## 4.1 Country-Level Analysis

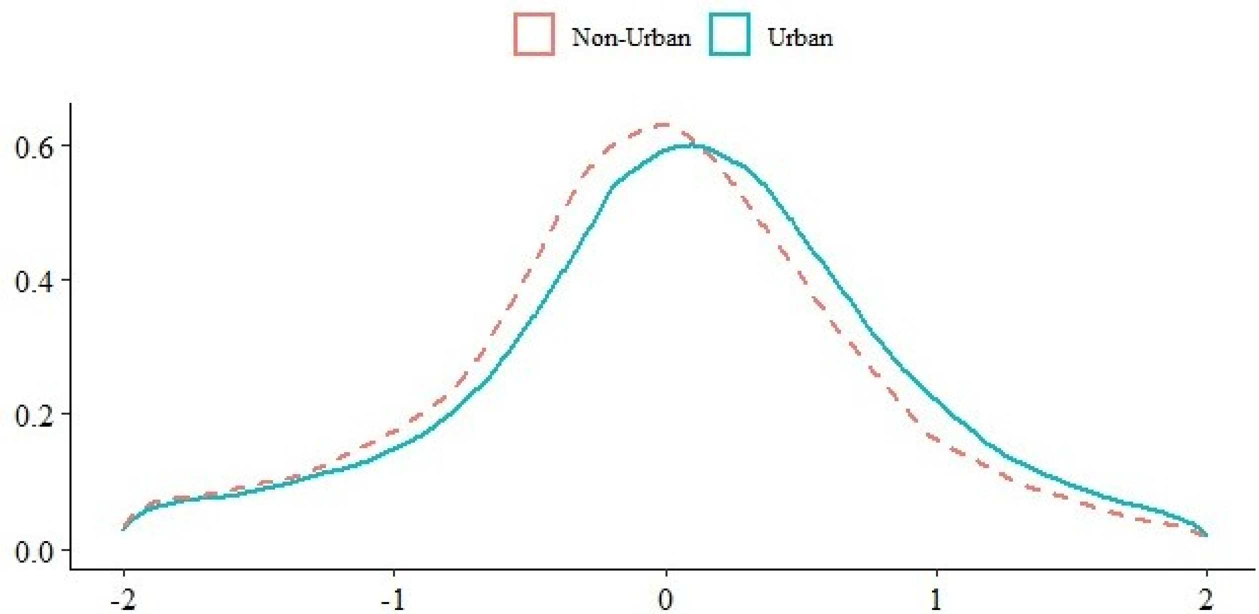
Table 2 shows the estimation results in our baseline sample. When aggregating across all industries in Australia, we find that the estimated parameters are $\hat{A} = 0.0654$, $\hat{D} = 1.1057$ and $\hat{S} = 0.0019$, and that these are all statistically significant.[17] The first two values provide evidence of agglomeration at the country-level. Turning to the selection parameter, note that this is a factor of the share of entrants eliminated by selection in urban relative to non-urban areas (see (4)).[18] Accordingly, while our estimate of $S$ is statistically significant, selection effects turn out to be economically small: only less than 0.19% of the firms are eliminated by tougher competition in urban vs non-urban locations. In sum, agglomeration rather than selection drives the differences in TFP across firm locations, which is in line with the findings in Combes et al. (2012) who use French data.

Based on our estimates, we can conclude that firms in urban cities are, on average, approximately 6.8% more productive than their regional counterparts. This number, which

[17]Significance tests are conducted based on bootstrapped standard errors. The last column in the table reports a pseudo-$R^2$, which corresponds to the mean-squared quantile difference between urban and non-urban distributions explained by our estimations (see Combes et al. (2012) for details).

[18]The corresponding factor of proportionality is given by $\frac{1}{1-S_{\mathcal{R}}} \geq 1$, which is the reciprocal of the share of surviving firms in non-urban areas.

**Figure 2:** Urban and Non-Urban TFP distributions




we refer to as the "urban advantage", is reported in the second column of 2.[19]

To better grasp the source of the urban advantage in Australia, Figure 2 shows the kernel density estimate of the distribution of log TFP of businesses for urban vs non-urban areas for the country as a whole. Simple observation of Figure 2 shows clear evidence of agglomeration effects as the distribution of the TFP for businesses in urban areas appears shifted to the right, consistent with an estimated parameter $\hat{A}$ that is positive. In this figure, such benefits seem to be more pronounced for high-productivity firms, that is, the distribution of TFP appears more dilated, in accordance with an estimated parameter $\hat{D}$ that is positive and above unity. However, note that the distribution of productivities does not appear to be more truncated for urban businesses than for rural ones. In fact, there does not seem to be left-truncation in either case, which is in line with an estimated parameter $\hat{S}$ that is close to zero.

[19] The urban advantage is approximated as $e^{\hat{A}} - 1$, i.e., the percentage difference in mean firm's productivity between urban and non-urban areas, assuming a selection parameter of zero.

**Table 3:** Country-Level Estimates for Selected Industries.

| Industry | Urban Advantage | $\hat{A}$ | $\hat{D}$ | $\hat{S}$ | $R^2$ |
|---|---|---|---|---|---|
| Professional, Scientific and Technical Services | 8.7% | 0.0831 | 1.0766 | 0.0013 | 0.95 |
| | | (0.0024)*** | (0.0046)*** | (0.0003)*** | |
| Wood and Paper | 7.6% | 0.0730 | 1.0558 | 0.0067 | 0.85 |
| | | (0.0068)*** | (0.0305)* | (0.0029)** | |
| Textiles and Furniture | 6.9% | 0.0666 | 0.8976 | -0.0051 | 0.82 |
| | | (0.0055)*** | (0.0173)*** | (0.0013)*** | |
| Metal and Metal Products | 5.6% | 0.0542 | 0.9274 | -0.0006 | 0.81 |
| | | (0.0044)*** | (0.0153)*** | (0.0014) | |
| Transport Equipment and Machinery | 5.4% | 0.0527 | 1.0043 | -0.0001 | 0.86 |
| | | (0.0060)*** | (0.0174) | (0.0011) | |
| Chemicals, Polymers and Minerals | 2.6% | 0.0261 | 0.9360 | -0.0035 | 0.59 |
| | | (0.0078)*** | (0.0238)*** | (0.0015)** | |
| Printing | 1.8% | 0.0174 | 1.0789 | -0.0005 | 0.66 |
| | | (0.0109) | (0.0314)** | (0.0027) | |
| Food, Beverage and Tobacco | -1.0% | -0.0101 | 0.9568 | -0.0005 | 0.46 |
| | | (0.0046)** | (0.0163)*** | (0.0013) | |
| Petroleum | -9.5% | -0.0996 | 0.8713 | -0.0992 | 0.98 |
| | | (0.0504)** | (0.1163) | (0.0409)** | |

Bootstrapped standard errors are reported in parentheses. ***, **, and * indicate significance above 1%, 5%, and 10%, respectively, under the null hypothesis of $A = 0$, $D = 1$ or $S = 0$, depending on the column.

Going back to Table 2, it is evident that results vary substantially across industry sectors. In particular, most of the urban advantages are accrued by firms in the service sector compared to manufacturing, as reflected by a much larger estimate of $A$ in the former sector. The analysis also reveals that the dilation parameter is above one for services, while it is below one in manufacturing. That is, firms in the service sector benefit the most from the urban advantages, and there may be signs of congestion in manufacturing whereby the most productive firms may not benefit as much from being located in denser urban areas. Firm selection parameters for services and manufacturing are close to zero, though significant, in line with our earlier estimates for all sectors.

In Table 3 we provide a more detailed sectoral analysis by focusing on specific industries, sorted in terms of the strength of their urban advantages. There is considerable variation in the latter. Urban advantages are the largest for businesses in the Professional, Scientific and Technical Services industry, and the lowest in the Petroleum and in the

Food, Beverage, and Tobacco industries. Those sectors, displaying *negative* advantages, would seem to benefit from being located in non-urban areas.

To conclude this section, we explore the urban advantage at the country-level by splitting the sample into "mature" and "young" firms. The former are defined as those businesses which have been established for more than three years; the rest of the firms in the sample are defined as "young" firms. The are two rationales for studying the interaction between firm age and urban productivity advantages. First, in the baseline model described in Section 2, firms draw their productivity before they start production. However, in reality, it takes time for a firm to learn their productivity and then decide whether they continue with production. In other words, firm selection is immediate in the model while it takes time in the real world. Then, focusing on mature firms may provide a more clear picture of the selection effect. Second, separating the effects by mature vs young firms may inform about who accrues the urban advantages and how such advantages affect firms over their life-cycle.

**Table 4:** Country-Level Estimates across Firm Ages.

| Age | Sector | Urban Advantage | $\hat{A}$ | $\hat{D}$ | $\hat{S}$ | $R^2$ |
|---|---|---|---|---|---|---|
| Mature | All Sectors | 7.7% | 0.0746 | 0.0017 | 0.0013 | 0.9259 |
| | | | (0.0017)*** | (0.0046)*** | (0.0002)*** | |
| | Services | 9.1 % | 0.0866 | 1.0672 | 0.0014 | 0.9373 |
| | | | (0.0029)*** | ( 0.0047)*** | (0.0005)*** | |
| | Manufacturing | 6.0 % | 0.0579 | 0.9271 | -0.0013 | 0.8308 |
| | | | (0.0024)*** | ( 0.0088)*** | (0.0006)** | |
| Young | All Sectors | 2.1% | 0.0208 | 1.1520 | 0.0029 | 0.9038 |
| | | | (0.0037)*** | (0.0084)*** | (0.0005)*** | |
| | Services | 5.4 % | 0.0522 | 1.1170 | 0.0014 | 0.8951 |
| | | | (0.0054)*** | ( 0.0094)*** | (0.0006)** | |
| | Manufacturing | -2.3 % | -0.02328 | 1.0447 | 0.0013 | 0.7829 |
| | | | (0.0070)*** | (0.01598)*** | (0.0007)* | |

"Mature" ("Young") firms are those which are older (younger) than three years since establishment date. Bootstrapped standard errors are reported in parentheses. ***, **, and * indicate significance above 1%, 5%, and 10%, respectively, under the null hypothesis of $A = 0$, $D = 1$ or $S = 0$, depending on the column.

Table 4 shows the results by firm age at the country-level. According to the table, the urban advantage is benefitting mature firms much more than young firms. This happens both in manufacturing as well as in the service sector. The difference in agglomeration effects across ages is largest in manufacturing, where agglomeration effects become negative and significant for young firms. Most selection effects are positive (except for manufacturing) and significant, but again close to zero. Interestingly, dilation is stronger among young firms under all specifications. This indicates that *gazelles* (i.e, high-growing and very productive young firms) may be benefiting greatly from being located in an urban environment.

**Table 5:** State-Level Estimates.

| Sector | State | Urban Advantage | $\hat{A}$ | $\hat{D}$ | $\hat{S}$ | $R^2$ |
|---|---|---|---|---|---|---|
| All Sectors | NSW | 7.7% | 0.0742 | 1.1190 | 0.0023 | 0.94 |
| | | | (0.0027)*** | (0.0091)*** | (0.0006)*** | |
| | VIC | 6.6% | 0.0639 | 1.1073 | 0.0011 | 0.94 |
| | | | (0.0073)*** | (0.0091)*** | (0.0007) | |
| | QLD | 4.6% | 0.0454 | 1.0927 | 0.0016 | 0.93 |
| | | | (0.0039)*** | (0.0095)*** | (0.0006)*** | |
| | SA | 1.5% | 0.0147 | 1.0854 | 0.0004 | 0.75 |
| | | | (0.0068)*** | (0.0163)*** | (0.0015) | |
| | WA | 10.0% | 0.0955 | 1.1238 | 0.0014 | 0.87 |
| | | | (0.0075)*** | (0.0123)*** | (0.0013) | |
| Services | NSW | 11.7% | 0.1106 | 1.0704 | 0.0006 | 0.94 |
| | | | (0.0048)*** | (0.0109)*** | (0.0007) | |
| | VIC | 8.1% | 0.0778 | 1.0822 | 0.0008 | 0.95 |
| | | | (0.0052)*** | (0.0087)*** | (0.0008) | |
| | QLD | 4.1% | 0.0403 | 1.0817 | 0.0016 | 0.92 |
| | | | (0.0046)*** | (0.0106)*** | (0.0006)*** | |
| | SA | 1.6% | 0.0154 | 1.0406 | -0.0007 | 0.43 |
| | | | (0.0107) | (0.0203)*** | (0.0022) | |
| | WA | 13.5% | 0.1267 | 1.0935 | 0.0005 | 0.87 |
| | | | (0.0096)*** | (0.0151)*** | (0.0017) | |
| Manufacturing | NSW | 2.4% | 0.0233 | 0.9690 | -0.0021 | 0.76 |
| | | | (0.0034)*** | (0.0126)*** | (0.0008)*** | |
| | VIC | 4.4% | 0.0431 | 0.9840 | -0.0007 | 0.78 |
| | | | (0.0047)*** | (0.0138) | (0.0008) | |
| | QLD | 5.1% | 0.0496 | 0.9563 | -0.0008 | 0.83 |
| | | | (0.0052)*** | (0.0155)*** | (0.0011) | |
| | SA | 3.3% | 0.0327 | 0.9655 | 0.0011 | 0.64 |
| | | | (0.0065)*** | (0.0233) | (0.0016) | |
| | WA | 4.6% | 0.0451 | 0.9042 | -0.0068 | 0.73 |
| | | | (0.0085)*** | (0.0229)*** | (0.0020)*** | |

Bootstrapped standard errors are reported in parentheses. ***, **, and * indicate significance above 1%, 5%, and 10%, respectively, under the null hypothesis of $A = 0$, $D = 1$ or $S = 0$, depending on the column.

## 4.2 State-Level Analysis

How do our previous results vary by state? Table 5 reports the estimated parameters by state and by sector aggregated as either manufacturing or services. Using all industries in the sample, we find large differences in urban advantages ranging from 1.5% in SA to 10% in WA. The values of our estimates across states are overall consistent with our findings from Section 4.1. Namely, for all states, agglomeration effects are positive and significant, the estimated dilation parameter is above one and significant, and selection is close to zero in all cases and often non-significant.

Breaking the results into manufacturing and services provides further insights into the factors affecting the productivity advantages in urban locations. Notably, relative advantages of industries vary dramatically across states. For example, urban advantages are twice as large for manufacturing firms in QLD (5.1%) vs NSW (2.4%) while they are nearly three times as large for service firms in NSW (11.7%) vs QLD (4.1%). Agglomeration effects are positive and significant for both manufacturing and services in most states. However, the service sector accrues the largest urban advantages in WA, NSW, and VIC, while manufacturing display the largest advantages in QLD, WA and VIC. The direction of the dilation parameter is significantly above (below) one for services (manufacturing) in each state, as it occurred in the country-level analysis (see Table 2).

Finally, Tables 6 and 7 illustrate the effect of firm age across states for firms within the service and manufacturing sectors, respectively. Our country-level previous conclusions on the effect of firm age also extend to the state-level analysis: within each state, productivity advantages are largely accrued by mature firms, and young firms may even be prone to urban disadvantages in NSW and VIC. The latter provides evidence of congestion in the main capital cities of Sydney and Melbourne. In addition, dilation is relatively stronger for young firms in the services sector, and the dilation parameter is consistently below one for mature manufacturing firms.

**Table 6:** Sate Level Estimates across Firm Ages
for the Service Sector.

| **Age** | **State** | **Urban Advantage** | $\hat{A}$ | $\hat{D}$ | $\hat{S}$ | $R^2$ |
|---|---|---|---|---|---|---|
| Mature | NSW | 11.3% | 0.1068 | 1.0748 | 0.0025 | 0.93 |
| | | | (0.0048)*** | (0.0095)*** | (0.0009)*** | |
| | VIC | 9.3% | 0.0886 | 1.0477 | -0.0004 | 0.95 |
| | | | (0.0054)*** | (0.0081)*** | (0.0010) | |
| | QLD | 4.9% | 0.0475 | 1.0790 | 0.0025 | 0.89 |
| | | | (0.0056)*** | (0.0114)*** | (0.0009)*** | |
| | SA | 4.6% | 0.0449 | 0.9983 | -0.0047 | 0.74 |
| | | | (0.0110)*** | (0.0199) | (0.0026)* | |
| | WA | 13.9% | 0.1304 | 1.0953 | 0.0016 | 0.84 |
| | | | (0.0129)*** | (0.0210)*** | (0.0026) | |
| Young | NSW | 9.1% | 0.0874 | 1.1179 | 0.0010 | 0.92 |
| | | | (0.0083)*** | (0.0205)*** | (0.0013) | |
| | VIC | 4.6% | 0.0452 | 1.1237 | 0.0010 | 0.83 |
| | | | (0.0131)*** | (0.0216)*** | (0.0015) | |
| | QLD | -0.3% | -0.0025 | 1.1110 | 0.0017 | 0.80 |
| | | | (0.0093) | (0.0151)*** | (0.0010)* | |
| | SA | -8.8% | -0.0921 | 1.2090 | 0.0030 | 0.71 |
| | | | (0.0251)*** | (0.0452)*** | (0.0058) | |
| | WA | 14.1% | 0.1316 | 1.1263 | -0.0002 | 0.94 |
| | | | (0.0185)*** | (0.0279)*** | (0.0029) | |

"Mature" ("Young") firms are those which are older (younger) than three years since establishment date. Bootstrapped standard errors are reported in parentheses. ***, **, and * indicate significance above 1%, 5%, and 10%, respectively, under the null hypothesis of $A = 0$, $D = 1$ or $S = 0$, depending on the column.

**Table 7:** Sate Level Estimates across Firm Ages
for the Manufacturing Sector.

| Age | State | Urban Advantage | $\hat{A}$ | $\hat{D}$ | $\hat{S}$ | $R^2$ |
|---|---|---|---|---|---|---|
| Mature | NSW | 4.6% | 0.0452 | 0.9540 | -0.0008 | 0.78 |
| | | | (0.0033)*** | (0.0117)*** | (0.0010) | |
| | VIC | 6.9% | 0.0670 | 0.9316 | -0.0004 | 0.85 |
| | | | (0.0050)*** | (0.0209)*** | (0.0021) | |
| | QLD | 6.7% | 0.0649 | 0.9390 | 0.0013 | 0.80 |
| | | | (0.0051)*** | (0.0147)*** | (0.0015) | |
| | SA | 4.4% | 0.0430 | 0.8986 | -0.0040 | 0.75 |
| | | | (0.0058)*** | (0.0243)*** | (0.0018)** | |
| | WA | 6.0% | 0.0579 | 0.8884 | -0.0069 | 0.80 |
| | | | (0.0088)*** | (0.0234)*** | (0.0022)*** | |
| Young | NSW | -4.8% | -0.0493 | 1.0723 | 0.0013 | 0.80 |
| | | | (0.0095)*** | (0.0263)*** | (0.0020) | |
| | VIC | -3.8% | -0.0390 | 1.0913 | 0.0041 | 0.71 |
| | | | (0.0121)*** | (0.0359)** | (0.0022)* | |
| | QLD | 0.8% | 0.0078 | 1.0716 | 0.0021 | 0.57 |
| | | | (0.0121) | (0.0263)*** | (0.0016) | |
| | SA | 0.7% | 0.0074 | 1.0619 | 0.0028 | 0.35 |
| | | | (0.0188) | (0.0508) | (0.0046) | |
| | WA | -0.2% | -0.0020 | 0.9862 | -0.0041 | 0.41 |
| | | | (0.0178) | (0.0375) | (0.0038) | |

"Mature" ("Young") firms are those which are older (younger) than three years since establishment date. Bootstrapped standard errors are reported in parentheses. ***, **, and * indicate significance above 1%, 5%, and 10%, respectively, under the null hypothesis of $A = 0$, $D = 1$ or $S = 0$, depending on the column.

# 5 Conclusions

We study the urban productivity advantages in Australia and find that they are driven largely by agglomeration externalities rather than selection effects. We also quantify these productivity advantages and find that, as a whole, the average firm in a major city is 6.8% more productive than the average firm in a regional/rural area in Australia. The results vary considerably by state and by sector. In NSW, this advantage is 7.7% whereas it is only 1.5% in SA. For manufacturing, the urban advantage is highest in QLD (5.1%) and lowest in NSW (2.4%). There is some evidence of congestion effects for young manufacturing firms in large cities such as Melbourne and Sydney.

Our results are important for regional development policies as we measure the opportunity cost in terms of productivity losses of incentivising firms to locate in rural areas. Importantly, by identifying the industries and states for which productivity losses from relocation are the smallest, our findings provide valuable inputs for formulating efficient regional policies.

There are a number of important issues that this paper leaves for future research. In particular, we are silent in terms of the many advantages associated with a more resilient non-urban economy. Such advantages may come from improved housing affordability, reduced migration costs and increased capacity to manage outbreaks during a pandemic, such as COVID-19.

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# Appendix

## A Details on the Estimation Approach

In this appendix, we provide further details on how to implement the estimation of the model presented in Section 2.2. Let $\theta = (A, D, S)$, and define the error

$$m_\theta(q) = \lambda_{\mathcal{U}}(\rho_S(q)) - D\lambda_{\mathcal{R}}(S + (1-S)\rho_S(q)) - A,$$

when comparing the quantile $q$ of the distribution of log productivity of city $\mathcal{U}$, against quantile $q$ of the modified distribution of log productivity of city $\mathcal{R}$. Similarly, let

$$\tilde{m}_\theta(q) = \lambda_{\mathcal{R}}(\tilde{\rho}_S(q)) - \frac{1}{D}\lambda_{\mathcal{U}}\left(\frac{\tilde{\rho}_S(q) - S}{1-S}\right) + \frac{A}{D},$$

denote the error when comparing the quantile $q$ of the distribution of log productivity of city $\mathcal{R}$, against the quantile $q$ of the modified distribution of log productivity of city $\mathcal{U}$, where $\tilde{\rho}_S(q) = \max\{0, S\} + [1 - \max\{0, S\}]q$.[20]

[20]The change of variables $q \to \tilde{\rho}_S(q)$ permits computing $\tilde{m}_\theta(q)$ for all quantiles $q \in [0,1]$ regardless of whether the selection parameter is positive or negative.

The estimate of $\theta$ is defined by

$$\hat{\theta} = \arg\min_{\theta} \left[ \int_0^1 \left(\hat{m}_\theta(q)\right)^2 dq + \int_0^1 \left(\hat{\tilde{m}}_\theta(q)\right)^2 dq \right], \tag{A.1}$$

where $\hat{m}_\theta(q)$ and $\hat{\tilde{m}}_\theta(q)$ are the empirical counterparts of $m_\theta(q)$ and $\tilde{m}_\theta(q)$, respectively. To numerically solve (A.1), we approximate the objective function using 1001 quantiles, and minimise it by applying the Nelder-Mead algorithm.