Are Labour-Managed Firms more resilient? Lessons from COVID-19 in the UK

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Abstract

Labour-Managed Firm (LMF) is an organisational type in which workers have the ultimate control over the firm and are residual claimants. This thesis presents new data on UK LMFs for the period 2012-2020 and compares differences in the way firms adjust employment and wage levels to changes in environment. We find that LMFs were less likely to cut jobs during the COVID-19 pandemic, while they were not more likely to decrease wages compared to traditional firms.

Contents

1 Introduction **3**
1.1 What is a Labour-Managed Firm (LMF)? . . . 3
1.2 Unique features of LMFs . . . 4
1.3 Why are LMFs rare? . . . 5
1.4 Social benefits of LMF enterprise . . . 6
1.5 Research question . . . 8

2 LMF behaviour: empirical research **8**
2.1 Major empirical studies . . . 8
2.1.1 Are LMFs more likely to stay in business during a crisis? 9
2.1.2 Are LMFs more likely to reduce employment or cut wages during a crisis? . . . 10
2.1.3 Variables of interest and differences in general firm characteristics . . . 12

3 Analysis of UK Cooperatives **13**
3.1 Data and method . . . 13
3.1.1 Data sources . . . 13
3.1.2 Legal forms and organisational types . . . 14
3.1.3 Data collection . . . 14
3.1.4 Analytical approach . . . 15
3.2 Empirical specification . . . 15
3.2.1 Employment model . . . 15
3.2.2 Wage model . . . 16
3.3 Results . . . 16
3.3.1 Descriptive statistics . . . 16
3.3.2 Results for the employment model . . . 20
3.3.3 Results for the wage model . . . 22
3.3.4 Assumptions and limitations . . . 23

4 Discussion **24**

5 Conclusion **25**

6 Appendix **28**

1 Introduction

There exists a wide variety of enterprise organisational forms. The modern capitalist firm is just one of them. Another organisational form that existed for centuries, and that recently started attracting more attention from empirical researchers, is the Labour-Managed Firm (LMF). In an LMF workers own the company and possess the ultimate control rights.

In this thesis, I present new data on UK Labour-Managed Firms for the period 2012-2020, including detailed information on company financials, including information on wages and employment.

The aim of the study is to compare the way LMF firms and capital-managed firms (KMFs) adjust their employment and wages in response to deteriorating economic conditions. The goal is to identify which organisational structure allows for firms that are more resilient, providing stable employment and income to people employed in the firm.

I start by providing the definition of a Labour-Managed Firm, focusing on how it differs from the modern capitalist enterprise. I then briefly introduce the theory of the Labour-Managed Firm and various empirical facts that require explanation, including the apparent rarity of such firms in most economies. After summarizing the major empirical works in the field, I conduct an analysis of UK LMFs using the Pooled OLS model and report the findings. I conclude with an assessment of differences in the way firms of two types adjusted their employment and wages during the COVID-19 pandemic of 2020, and evaluate how these differences translate into capacity of the firm to ensure job security.

1.1 What is a Labour-Managed Firm (LMF)?

A Labour-Managed Firm (LMF), sometimes called WMF (Worker-Managed Firm), or Employee-Owned Firm, is a firm where labour owners, workers, have ultimate control rights. Practical examples of this are worker (producer) cooperatives and partnerships. LMF is contrasted with a Capital-Managed Firm (KMF), a traditional capitalist enterprise, currently the most widespread type of firm worldwide. K in KMF stands for capital, a common notation in economics. LMF and KMF notation is borrowed from Dow, 2018[1]). WMF notation is used in Burdín, Dean, 2012[2]. Term "Employee-Owned Firm" is used e.g. in Ben-Ner et al., 1993[3]).

In a KMF, capital suppliers, such as investors or their representatives, hold control rights. "Control" here refers to any decision-making process not regulated by legally enforceable contracts, usually addressed by a combination of vote/bargaining. Since day-to-day decisions in firms are commonly made by appointed managers, it is important to define an "ultimate" group of controllers. An ultimate control group is the one that can hire and fire top managers, and therefore has the last say in firm-level decisions.

In this sense an LMF differs from a "hybrid" firm, a mixed organisation form that includes firms where workers participate in governance or have a share in firm ownership, but do not possess ultimate control rights. Examples of this are

Employee Stock Ownership Plans (ESOPs) in United States and companies with co-determination systems in Germany, Austria, and a number of other european countries (Jäger et al., (2021)[4]). It is argued by Dow that managers and/or capital owners have the last say in firm-level decisions in such organisations.

It is important to distinguish between two types of definitions of LMF: empirical and theoretical. Empirical definitions serve a practical purpose in research, and are used to include or exclude particular companies from a sample. They specify concrete legal forms associated with an LMF in given countries.

Theoretical definitions are much more broad, and do not point to specific legal forms. Instead, they define a firm in terms of organisational theory and comparative economics, and serve to differentiate between firms with different organisation and behaviour in the context of an economy. Only theoretical definitions are considered in this section. Empirical definitions for the UK case are developed in a later section to aid in constructing a dataset.

1.2 Unique features of LMFs

Organisational arrangements can differ between firms, but what unites all LMFs is:

1. Membership in the firm that is conditional on work contribution (labour)
2. Distribution of surplus is either conditional on, or proportional to, work contribution
3. Ultimate decision-making power belongs to workers, either directly when decisions are made via a voting process, or indirectly when workers can hire and fire top managers

Other features (e.g. one person, one vote rule or a ban on hiring waged workers) are arguably not defining features of an LMF, though there is no consensus in the literature about this. This analysis follows Dow.

An alternative view from Moene (1989)[5]) posits that presence of hired workers and decision-making that is not characterised by a one-person, one-vote rule are not compatible with a pure LMF. In practice, one of the biggest LMF firms in the world, the Mondragon corporation, hires non-member workers (Monasterio (2007)[6]). LMFs can also attract external investment, subject to a need for specialised contracts.

Fundamental differences between KMFs and LMFs can be attributed to many practical distinctions between labour and capital as a production input. For example, capital is alienable, meaning it can be transferred from one owner to another without losing its properties. In contrast, labour is not alienable, as skills and experience are characteristics unique to every given individual.

Membership in an LMF implies having a position of a worker-owner. Even though membership in LMFs is usually not traded, there exists literature exploring potential effects of introducing markets for LMF memberships.

Such markets are supposed to address specific organisational issues attributed to LMFs. One of the issues is insufficient hiring, with LMFs tending not to

increase employment with frequency or volumes required by market conditions and the firm objectives. Another issue is a negatively sloped supply curve, meaning the firm decreases its output when output price increases.
This applies, however, only to the so-called Ward-Domar-Vanek (WDV) firms: a term widely used in the literature to refer to LMFs that maximise income per worker. WDV firms are named after a trio of researchers who made early contributions to the field in 1958-1970.
Another type of LMF firm explored in theoretical research is a Sertel-Dow firm, in which membership is traded on a competitive market. This results in profit-maximising behaviour. Organisational issues highlighted for WDV firms don't apply to Sertel-Dow firms, as they behave in ways similar to that of profit-maximising firms.
Empirical data on LMFs, however, supports neither the Ward-Domar-Vanek nor the Sertel-Dow theories. Mixed objectives are often found to take place in practice, with LMFs maximising a combination of employment and income per worker.

1.3 Why are LMFs rare?

LMF firms exist in the real world, and number in thousands in many countries, but remain relatively rare in modern market economies compared to capitalist firms (Perotin (2014)[7]). Countries with the most LMFs in Europe are Italy and Spain, with Italy having 25,000 worker cooperatives in 2010, and Spain 18,000 in 2008.
As significant as these numbers are in absolute terms, they only comprise a minor share of the total number of firms. For example, Italian Lega (National League of Cooperatives and Mutual Aid Societies) commanded 2.73% of Italian GDP and 12.75% of GDP of Emilia Romagna, region with the strongest presence of LMF firms, in 1989, when there were 11,398 firms in the league (Dow (2003)[8]).
Even though they are rare, LMFs are not always small. A review by Perotin (Perotin, (2016)[9]) compares the size distribution of LMFs with that of conventional firms. Most firms in modern economies are small: the percentage of firms in UK employing less than 10 people is close to 93.7%. This number is 89.6% in the US and 90.4% in France.
LMFs are, on average, bigger than KMFs in terms of employment: average employment in Italy for was 284 for LMFs and 228 for KMFs in 1994, median employment was 153 for LMFs and 72 for KMFs. In France, proportion of firms with less than 6 employees was 69.3% for all firms together, and only 52% for worker cooperatives (a subset of LMFs) in 2007. However, percentage of LMFs in France that fall into the 6 to 19 employees bracket is bigger than the same percentage for all firms: 32.2% versus 21.1%. In Uruguay 64.1% of firms had less than 6 employees, and only 8.6% of worker cooperatives; though 24.4% of all firms had 6 to 19 employees, and this number was 75.8% for cooperatives.
Comparative rarity of LMFs is a fact that any LMF research needs to account for, since it has implications for how we view LMF behaviour. E.g. if LMFs

display similar or higher productivity compared to conventional firms, a fact confirmed by some of the studies in the field (Pencavel, Craig (1994)[10], Fakhfakh (2012)[11]), why are they not more prominent that KMFs? According to market principles, such firms would have an advantage over competitors. Moreover, if one assumes that LMFs are more productive, and consider a scenario where they become significantly more prominent, this should improve productivity across the economy.

Different explanations for aggregate LMF rarity are offered in the literature. These are explored in more detail in Dow (Dow (2018)[1]), below is a brief summary.

Workers usually don't have enough wealth to finance firm formation. Funds can be pooled by several workers, but this requires additional organisation, and the group faces collective choice problems, since it's hard for every individual worker to assess the probability of success or failure for a given venture. Moreover, workers preferences and objectives tend to be more heterogenous than investors', meaning it's harder for them to come to a consensus with regards practical questions that arise when setting up a firm, such as what it will produce, how it will be financed, etc. (Hansmann (1996)[12]).

Higher risk aversion of workers compared to investors is named as an obstacle to firm formation by Meade and Kihlstrom, Laffont and Dreze. Since workers are, on average, poorer, they are less willing to take risks, and taking risks is an essential part of launching a new business venture. Therefore, one can expect less new firms to be created by workers, and less conversions of existing KMFs to LMFs. The issue is further reinforced by membership being conditional on the worker supplying labour to the firm: worker-owners cannot diversify their labour investment across many firms to counter risk, as investors usually do.

Another line of reasoning focuses on incentives. Alchian and Demsetz explain the rarity of LMFs by pointing out that for teams to exclude shirking by individual team members, they need to employ a monitoring agent. To make sure this agent does not shirk either it makes sense to pay them the residual income of the firm instead of a wage. This is opposed by Putterman, who points out that members can monitor each other, and this is often more cost-effective than paying a dedicated monitoring agent. Monitoring can be excluded altogether by offering external motivation to workers, such as bonuses or penalties (as explained by Holmstrom). There are also potential issues that can arise with a monitoring agent, for example monitor can claim that worker effort is low when it's high, thus cheating, as Eswaran and Kotwal, MacLeod, Andolfatto and Nosal point out.

1.4 Social benefits of LMF enterprise

There are plenty of potential social benefits of LMF firms identified by different authors. These partially stem from different LMF firm objectives, and partially from characteristic features of LMF. Table 1 present a summary of major social benefits of LMF enterprise.

Main benefits explored here relate to employment and job quality, though distributional effects, like those explored by Estrin, 1991, can also play a beneficial role in reducing social inequality.
Fakhfakh (Fakhfakh (2012)[11]) reviews data on French worker cooperatives (SCOPs) for 1989-1996. Data on employment and job cuts of cooperatives is compared to that of conventional firms. Where differences are significant, authors report higher employment growth in KMFs in three industries versus in one industry in cooperatives, in times of cyclical upturn when market was growing. However, in times of recession or slowdown in growth, cooperatives were cutting jobs less fast than conventional firms, or even grew. In the same study, authors probe for differences in productivity by first establishing that production technology is different in cooperatives compared to KMFs, then testing for level of output that results when KMFs use cooperative technology, and vice versa. They find that cooperatives were more productive with their own technology in "almost all" cases, compared with scenarios where they use KMF technology. Higher productivity provides additional social benefits, as it implies higher output per unit of time, and therefore more efficient production.
Burdín and Dean (Burdín, Dean (2009)[13]) review the data for the case of a macroeconomic crisis in Uruguay in 1999-2002, and find that cooperatives were less likely to cut jobs than conventional firms. They were also more willing to adjust pay downward in response to the crisis.
With regards to distributional dynamics in LMFs, Estrin, 1991[14]) finds that different power dynamics and decision-making arrangements in cooperatives resulted in pay and employment setting patterns that are shifted in favour of lower-skilled blue-collar workers, while not favouring managers as much as KMFs. Managers in year 1985 in the dataset of Italian firms earned 30% less than managers in conventional firms, and were representing only half of their employment share in conventional firms.

Table 1 LMF Social Benefits

Identified in	Measure	Legal form	Country	Description
Burdín, Dean, 2009; Fakhfakh, 2012	Reduced job cuts	Cooperative	Uruguay, France	More likely to retain jobs facing crisis or external shock
Fakhfakh, 2012	Increased productivity with own technology	Cooperative	France	Produce more with own technology than with KMF technology
Estrin, 1991	Reduced skill and worker/manager pay gap	Cooperative	Italy	Income and jobs are redistributed away from white-collar workers towards less-skilled blue-collar workers

1.5 Research question

The aim of this thesis is to explore potential social benefits of LMFs in terms of income and job security. In particular, the focus is, to see whether worker cooperatives and other types of LMFs provided more stable and higher quality employment for workers, especially in times of crisis. Data on LMFs in the United Kingdom for years 2012-2020 is studied. See section 4.1 for details on what choices and assumptions were made when assembling the dataset. The research question can be defined as: **"Do cooperatives and other Labour-Managed Firms in the UK provide employment that is more resilient to external shocks, compared to conventional firms?".**
This research question is further broken down into sub-questions:

(Q1) Are LMFs in the UK more or less willing to adjust employment levels in response to changes in relative output prices compared to KMFs?
(Q2) Are LMFs in the UK more likely to reduce pay in times of recession or after suffering an output price shock?
(Q3) Did the employment decrease in LMFs during the COVID-19 pandemic, and if so, was the magnitude of the decrease higher or lower than that for KMFs?

The hypotheses tested in the empirical section of this thesis are as follows:

(H1) Employment responses to changes in relative output price are less elastic in LMFs compared to KMFs
(H2) Wages in LMFs are more sensitive to changes in relative output price compared to KMFs
(H3) Magnitude of the decrease in wages was higher in LMFs compared to KMFs in 2020, at the outset of the COVID-19 pandemic
(H4) Magnitude of the decrease in employment was lower in LMFs compared to KMFs in 2020

I hypothesise that LMFs in UK, on average, provide more stable employment, but may be prone to reduce pay in times of crisis or when suffering price shocks.

2 LMF behaviour: empirical research

2.1 Major empirical studies

This section provides an overview of prominent empirical work on LMF behaviour to date. I focus on empirical studies in this review. A comprehensive theoretical framework modeling comparative static behaviour of Labour-Managed Firms on the market and offering an explanation for various empirical asymmetries, including the rarity of LMFs, is provided in Dow, 2018 [2].
Research on LMF firms is relatively scarce. Table 2 summarizes major empirical studies on the topic in terms of research setting, data employed, and the characteristics of the sample. In what follows, I elaborate on the findings of

these studies, starting with an overview of the differences in firm exit rates for LMFs and KMFs, then comparing employment and wage adjustment dynamics, and finally identifying differences in general firm characteristics which might have a bearing on the results. The aim is to provide a high-level view of firm behaviour and determine whether the way LMFs and KMFs adjust employment and wages in response to shocks is different based on the literature, accounting for features of both types of firms that are consistent across time and geographic location.

Table 2 Empirical studies

Author(s), Year	Research Setting	Data format	Sample
Panel data			
This study	UK firms, 2012-2020	annual micro-panel	25 LMFs/year on avg.
Monteiro N.P., Stewart G., 2013	Portuguese firms, 1995-2007	annual micro-panel	1106 LMFs/year on avg.
Burdín G., Dean A., 2012	Uruguayan firms, 1996-2005	monthly micro-panel	311 LMFs/year on avg.
Fakhfakh F., Pérotin V., Gago M., 2012	French cooperatives, 1987-2004	annual micro-panel	500 LMFs/year on avg.
Pencavel J., Pistaferri L., Schivardi F., 2006	Italian firms, 1982-1994	annual micro-panel	337 LMFs/year on avg.
Bartlett W., Cable J., et al., 1992	Northern Central Italy firms, 1981-1985	annual micro-panel	49 LMFs
Craig B., Pencavel J., 1992	U.S. Northwest Plywood cooperatives, 1968-1986	micro-panel	11 LMFs
Other data			
Arando S., Peña I., Verheul I., 2009	Basque country firms for 1995-2002	firm entries by industry, location	892 LMF entries
Podivinsky J., Stewart G., 2007	UK manufacturing firms for 1980-1985	firm entries by industry	1321 LMF entries

2.1.1 Are LMFs more likely to stay in business during a crisis?

The first question to consider when analysing differences in job security for LMFs and KMFs is whether there are differences in survival rates between different firms. If a firm closes when a crisis hits, it cannot provide any kind of employment, not to mention providing stable and gainful employment. Study by Burdin, 2013 [15] tackles this question using a sample of Uruguayan firms. Author finds that for LMFs the risk of dissolution is 25% lower than for KMFs, controlling for start-up size, average wage, and the cohort year. The period

analysed in the study (1999-2002) includes years of Uruguayan economic crisis, which is considered by author to be one of the potential explanations for the large difference in outcomes: some of the theories in the literature suggest LMF entry and exit to be counter-cyclical, meaning LMF firms might actively enter the market in crisis and exit in good times.
In Pérotin, 2006 [16], author calculates average exit rates for LMFs and conventional firms. The average exit rate for LMFs is 10% over the period 1979-2002. Average exit rate for KMFs is 11%. The general entry and exit behaviour of LMFs is found to be similar to that of KMFs, with higher rates of exit during recessions and periods when interest rates were high, an argument against the counter-cyclical entry hypothesis.
Monteiro, Stewart, 2013 [17] analyse firm survival on a large panel of Portuguese firms, with annual data for years 1995-2007. The data set contains information on firm characteristics, such as firm age, employment, gender ratio, as well as information on regional and industry distribution. Authors include industry-specific variables, such as entry costs and volatility. Estimating a Kaplan-Meier survival function, authors find that 97% of LMFs and 80% of KMFs survived for 5 years or more over the period. 84% of LMFs and 45% of KMFs survived for 20 years or more. 63% of LMFs and 20% of KMFs survived for 50 years or more. It is important to note that due to the nature of the estimation, long-lived firms are over-represented in the results for both types of firms.

2.1.2 Are LMFs more likely to reduce employment or cut wages during a crisis?

Given that exit rates of LMFs seem to be similar or lower of those found in KMFs, one might assume LMF firms are at least as resilient as their conventional counterparts. Another component of resilience is how firms respond to changes in their environment in terms of changing their employment and wage level. Thus, it is important to compare the way both types of firms adjust employment and wages in unfavourable times.
An important proxy for changes in environment, namely product market shocks, is output price in a particular industry relative to the rest of economy. This captures changes in product market specific to a given industry.
In Craig, Pencavel, 1992 [18], authors analyzed the data on U.S. Pacific Northwest firms in the plywood industry over the year 1968-1986. Employment is regressed on output prices, taking work hours into account. Authors find that for LMFs the change in output prices did not affect employment or work hours, but had a positive effect on hourly income.
Burdín, Dean, 2012 [13] explore a long monthly panel of Uruguayan firms for years 1996-2005, with information on wages, employment, and member to employee ratios. Empirical approach follows Pencavel, 2006 [19], with regressions that feature lags of dependent variable and various robustness checks, such as conducting regressions only for manufacturing firms. Authors find that LMFs and KMFs employment and wages followed different patterns during

the 2002 financial crisis in Uruguay. In fact, in 2003, immediately following the market shock, employment in LMFs averaged 106% of the 1998 level, whereas employment in KMFs amounted to only 87% of the 1998 level. Wages were more likely to adjust in LMFs compared to KMFs, with wage gap growing between 1996 and 2001 and then returning back to original values. Authors also test the degeneration hypothesis, testing theories suggesting that LMFs "degrade" into KMFs over time due to perverse incentives. No evidence for the existence of the degeneration problem is found for Uruguayan firms in the dataset. Fakhfakh, Pérotin, Gago, 2012 [11] assemble data on French SCOPs (a legal form for cooperative enterprise) for the period 1987-2004 and combine it with data on KMFs from surveys collected by INSEE, the French statistical office. Cooperatives with less than 20 employees were removed from the data. Authors find that LMFs cut jobs less actively, or even add jobs, during the period in the data set which includes a recession. In a different data set that includes a period of moderate growth, KMFs were growing more actively in three industries, and LMFs only in one industry. This suggests that LMFs may be more resilient in times of crisis, but KMFs may add jobs faster in good times.

Pencavel, Pistaferri, Schivardi, 2006 [19] use annual data on companies from the Italian Company Accounts Data Service. Within-group specification is used to investigate the differences in wage, employment and capital dynamics between KMFs and LMFs. Authors find that employment was less volatile in LMF and wages more volatile. LMFs had, on average, 14% lower wages compared to KMFs. Partial correlation between wages and employment was found to be close to zero, and LMFs with higher wages had higher capital. In general, findings of the study support the hypothesis that LMFs protect employment of workers from external market shocks.

Bartlett, Cable, 1992 [20] study the LMFs in Toscana and Emilia-Romagna regions of North-Central Italy. All the firms in the sample are in the light manufacturing sector that comprises 10% of producer cooperatives in the region, though the authors suggest that results can be generalized to services and construction. Firms were matched by size and industry, and differences in wage levels, employment, productivity and labour relations were estimated. Results indicate that average employment in LMFs is more stable, with coefficient of variation being 0.011 for LMFs and 0.015 for KMFs. During a period of adverse economic conditions in 1981-1985 both types of firms experienced job loss, but for KMFs the employment levels were declining throughout the whole period, whereas for LMF employment stabilised towards 1984, and increased between 1984 and 1985.

Aside from estimations that employ panel data, a section of studies considers firm entry and exit rates across industries to answer questions about the differences in LMF and KMF market entry and exit.

Arando, Peña, Verheul, Stewart, 2009 [21] explore the relationship between market environment, changes in legal setting within the country, and firm characteristics with regards to market entry. Authors conduct OLS regressions on the data and calculate Pearson correlation coefficients. Model specification includes variables to capture the effect of changes in both formal and informal institutional conditions. Authors find that LMF entry is counter-cyclical, meaning that such firms tend to enter the market in periods of adverse economic conditions, and exit in better times. What is interesting is that authors find a similar pattern for publicly traded firms. Authors also identify that presence of "embedded cooperative culture" in a location, measured as share of cooperatives in the total number of firms, also contributes positively to LMF firm creation.

Podivinsky, Stewart, 2007 [22] study specifically aimed at answering the question of rare LMF entry for UK manufacturing firms. Firm entry is measured by VAT registrations and grouped by industry. A Poisson model is applied as a baseline approach, and a negative binomial model is used to deal with overdispersion. Authors find significant negative effects of capital-labour ratio on firm entry, meaning LMF firms are less likely to enter where capital-labour ratio is higher, and significant positive effects of industry sales. Findings confirm that low LMF entry may be related to problems with raising finance and coping with risk.

2.1.3 Variables of interest and differences in general firm characteristics

Based on the literature, main variables affecting employment level are lag employment, wage level, and relative output price. It is also important to control for industry and firm size, as this not only influences firm entry, as suggested in Arando, Peña, Verheul, Stewart, 2009 [21], but also suggests different production technologies (Fakhfakh, Pérotin, Gago, 2012 [11]) and product market conditions (Pencavel, Pistaferri, Schivardi, 2006 [19]). I examine how size and industry distributions differ between LMFs and KMFs in practice, according to existing studies.

LMFs tend to be concentrated in labour-intensive industries. Pencavel, Pistaferri, Schivardi, 2006 find that LMFs are concentrated in construction, transport and services in Northern Italy. Fakhfakh, Pérotin, Gago, 2012 [11] share industry distributions for France, with LMFs concentrated in manufacturing and construction, with a growing share in services.

Arando, Peña, Verheul, Stewart, 2009 [21] find that LMFs are more likely to exist in manufacturing, with support for the importance of regional agglomeration. Podivinsky, Stewart, 2007 [22] find a high degree of industry concentration in UK manufacturing LMFs. The following industries accounted for 90% of registrations over the period studied: Other Manufacturing (including clothing and printing), Distribution, Hotels, Catering and Repairs (including food retailing and restaurants).

Wage distribution can also potentially have effects on firm hiring decisions, and has a bearing on the social benefits of firms of a given type, as firms with more equal wage distributions are arguably more beneficial to the broader society than those where wages are concentrated, say, at the top. In Estrin,

1991, author finds that an average LMF worker works largely in blue-collar occupations. There are less managers in LMFs, and the salaries of managerial staff are lower. Earnings of LMF managers comprise roughly two-thirds of the earnings of managers in KMFs. LMF managers employment is only half the employment level of KMF managers. Wages of the lowest paid workers, however, were found to be essentially the same as in capitalist firms.
This is contested in Burdín, 2016 [23]. The author used a sample based on Uruguayan social security data that covers an average of 40,000 workers per month. Even though an average worker employed by an LMF earns between 2.7% to 9% more than a KMF worker, based on estimates of a Pooled OLS regression with different specifications, the wage premium is concentrated at the bottom. In 2009, the wage premium for a worker in the 0.2 quantile of the wage distribution was 18%, whereas a worker in the 0.8 quantile would experience a penalty of 4%.
Clemente, Diaz-Foncea, Marcuello, Sanso-Navarro, 2012 [24] further elaborate on the question of LMF wage distribution. The sample in the study is based on Spanish social security records and includes data on 544,671 workers, with 8,880 employed in LMFs. Authors of this study distinguish between "worker-owned" cooperative firms where workers set the wage, and "non worker-owned" firms where workers do not set the wage. For the general sample, the log wage is higher in KMFs compared to worker-owned cooperatives, with the values being 11.89 and 11.84 respectively. However, the log wage in KMFs is lower than in non worker-owned cooperatives, the value for non-worker owned firms being 11.90.

3 Analysis of UK Cooperatives

I contribute to empirical research on the differences between adjustment responses of LMFs and capitalist firms to crises by introducing new data on labour-managed firms in the United Kingdom for the period between year 2012 and year 2020. A panel data set is assembled by matching organisational data from Co-operatives UK [25] and financial data from Companies House, the UK company register. The data set is then extended with information on KMFs from Amadeus [26], producer and consumer price indices to get annual snapshots of LMF and KMF financial performance. I then conduct descriptive analysis, run panel data regressions to find differences in behaviour of KMFs and LMFs, and interpret the results, focusing on implications of empirical asymmetries on job quality and social benefits of enterprise.

3.1 Data and method

3.1.1 Data sources

I use Co-operatives UK open organization and economic data sets to assemble a list of LMFs in the UK adhering to empirical definitions. Co-operatives UK is a network of UK co-operative organisation founded in 1870 under the name

"Co-operative Central Board". According to the network's website, it includes "thousands of co-operatives". The data set was assembled with the aim of monitoring all co-operatives in the country, not just those in the network. I match basic data on LMF companies, as well as the number of memberships and employees from both Co-operatives UK data sets with detailed financial data from Companies House using a business information platform called Endole [27]. For data on KMFs, I use the Amadeus database that contains both basic data on companies and financial data, including number of employees, remuneration, fixed assets and value added for each firm. Total firm remuneration is denoted as "Employee costs" in this database. I retrieve data on producer price index (PPI), service producer price index (SPPI), and consumer price index (CPI) from ONS, the UK statistical office. These indices don't include firms in Construction, Agriculture sectors.

3.1.2 Legal forms and organisational types

Data on firms with different legal forms is provided by different authorities in the UK. Specifically, data on firms with legal forms being one of Company, Community Interest Company and LLP is managed by the Companies House. Data on Co-operative and Community Benefit societies, including the Co-operative society legal form, is administered by the Financial Conduct Authority (FCA). The data in this thesis only pertains to firms registered with Companies House, as it was readily available. This means only firms with the legal forms of Company, Community Interest Company (CIC), and LLP are included. Firms registered with FCA that are registered societies could be included in the dataset in the future, as the financial statements for such firms are publicly available in the Mutuals Public Register [28].
With regards to ownership classification, Co-operatives UK contains information on co-operatives broadly defined, including consumer and tenant co-operatives, and co-operatives of co-operatives. I only include co-operatives owned by either workers, self-employed or employee trusts in this study as these more closely match the definition of the Labour-Managed Firm described in the introduction. Unlike in Burdín, 2012 [13], even though information on the number of members and employees is available for some firms, I am not able to distinguish between changes in wages of members and employees in LMFs studied.

3.1.3 Data collection

Endole database was manually searched to retrieve Companies House data on each LMF firm and match with Co-operatives UK data. Companies House records were found for 409 firms, with the highest number of observations available in year 2019, immediately before the COVID-19 pandemic. Data on both the number of employees and total remuneration was only available for 59 LMF firms, these firms are used in empirical analysis. A total of 96713 unique KMF firms was included in the data. Financial data assembled comprises a total of 85 variables with observations across 2012-2020. Only information on

remuneration, number of employees, fixed and net current assets, profit and depreciation is used in panel data regressions. Average number of observations for the "Total remuneration" variable is 34.88, average for "Number of employees" variable is 111.11. Information for many of the variables available in the evidence, such as data on assets and liabilities, shareholder equity, reserves and inventory, was not used in this analysis due to the limited scope of the thesis. As only a minor portion of the indicators covered by this data was considered in existing research, including these indicators in the analysis provides potential ground for further studies on the topic. 46 variables had an average number of observations higher than 34.88, the value for "Total remuneration", indicating high availability of the data.
Table 3 shows the number of firms with data on remuneration and number of employees available for each year studied and the number of firms of each particular type.

Table 3 Data incidence count

Count	2012	2013	2014	2015	2016	2017	2018	2019	2020
Total	33548	36250	39491	43066	47003	51320	61533	70555	74991
KMF firms	33528	36227	39468	43042	46975	51294	61503	70525	74966
LMF firms	20	23	23	24	28	26	30	30	25

3.1.4 Analytical approach

My empirical strategy follows that of Pencavel (2006) [19] and Burdín (2012) [13]. I estimate panel data regressions using the Pooled OLS model, since the data is observed annualy and the number of observations does not allow to conduct random or fixed within-effects estimations. This means that unobserved heteoregeneity between firms is not accounted for in the model. As the data for remuneration is not available on the level of individual employees, average remuneration is calculated as:

$$w_{it} = \frac{W_{it}}{N_{it}} \tag{1}$$

Where in equation 1 N_{it} denotes the total number of employees for a company i in year t , and W denotes total remuneration. Table 12 lists definitions for each variable included in empirical models.

3.2 Empirical specification

3.2.1 Employment model

I use the following general model to test **H1**:

$$\ln E_{it} = \ln E_{it-1}\delta_0 + \ln E_{it-1}C_i\delta_1 + \ln w_{it}\eta_0 + \ln w_{it}C_i\eta_1 + \ln p_{it}\eta_2 + \ln p_{it}C_i\eta_3 + \lambda_{Control} + \beta_{E,it} + \mu_i + \epsilon_{it} \quad (2)$$

Where in equation 2 $\ln E_{it}$ is the natural logarithm of employment for company i in year t; $\ln E_{it-1}$ is the lag of the employment helping capture inertia effects of the way in which firms adjust employment; $\ln w_{it}$ is the natural logarithm of wage for company i in year t; $\ln p_{it}$ is the value of the output price index for the SIC sector corresponding to company i in year t; C_i is the dummy variable taking value 1 for LMFs and 0 for KMFs; $\beta_{E,it}$ is the effect of the LMF status on wage level, and μ_i denotes unobservable factors that affect employment and are fixed for a given firm over time, while varying between firms. Control variables for company size bracket, industry, and year are all included in model specification and denoted by vector $\lambda_{Control}$. Perfectly collinear variables are dropped from the model.

3.2.2 Wage model

The following model is used to test **H2** and **H3**:

$$\ln w_{it} = \ln w_{it-1}\alpha_0 + \ln w_{it-1}C_i\alpha_1 + \ln w_{it-2}\alpha_3 + \ln w_{it-2}C_i\alpha_4 + \ln p_{it}\gamma_0 + \ln p_{it}C_i\gamma_1 + \lambda_{Control} + \beta_{w,it} + \omega_i + \nu_{it} \quad (3)$$

Where in equation 3 $\ln w_{it}$ is the natural logarithm of wage; $\ln w_{it-1}\alpha$ and $\ln w_{it-2}\alpha$ are first and second logarithm lags of wage, respectively; C_i is the dummy taking value 1 for LMFs; $\ln p_{it}$ is, similar to equation 2, the value of the output price index for the relevant SIC sector; $\beta_{w,it}$ is the effect of the LMF status on the wage level, and ω_i is a variable denoting unobservable factors that affects wages and are fixed for a given firm over time but vary between firms. As in model 2, control variables for company size bracket, industry, and year included as the $\lambda_{Control}$ vector.

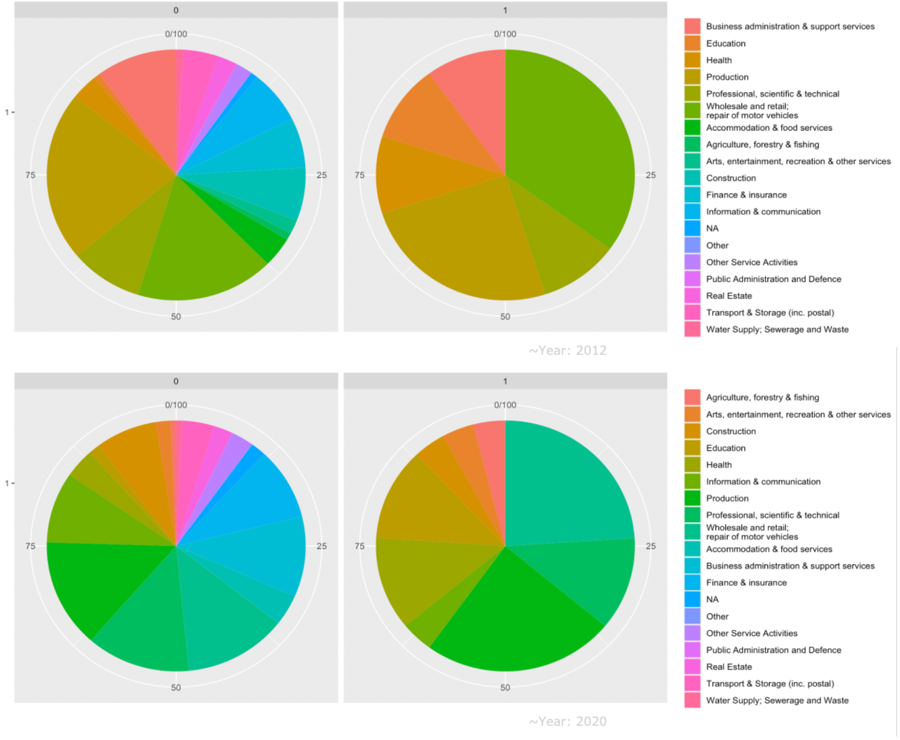
3.3 Results

3.3.1 Descriptive statistics

Descriptive statistics are reported in 4. Only years 2012, 2016 and 2020 are displayed. The size of the sample is very different between KMFs and LMFs. The highest number of observations, for which LMF financial data could be found as reported by Companies House, is 28 in 2016. The highest number of observations in the sample for KMFs as reported by Amadeus is 69,232 in 2020.
Figure 1 presents the distribution of firms across SIC sections for both types of firms. 0 denotes KMF firms and 1 denotes LMF firms. The sample contains firms across more SIC sections for KMFs across the whole period. The

distribution of LMF firms is skewed towards retail and production, and additionally towards health and education by 2020. Due to the fact that sample is

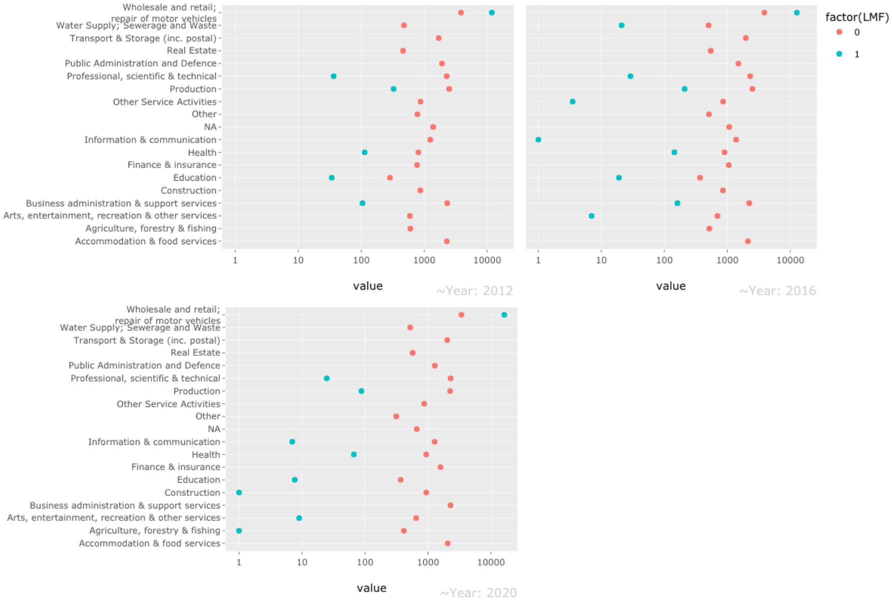
Fig. 1 Firm count by SIC Section



skewed towards larger companies for LMFs, the average employment observed is higher than would otherwise be expected across UK firms, with the average value being 546.96 for KMFs and 4256.4 for LMFs in 2012. Hence, total employment observed is comparatively large for our LMF sample: the highest value is 91,016 in year 2016. Employment standard error also differs, with KMFs having a standard error of 38.171 in 2012, the value for LMFs being 4086.782.

Higher average LMF employment does not hold when breaking the distribution by SIC section. Figure 2 shows average employment by section for selected years. LMF average employment is consistently lower than KMF for most SIC sections over the period, a result that can be in part attributed to the difference in the sample. The only exception to this is the average employment for wholesale and retail, which is consistently higher for LMFs. It is important to note that the share of firms in this SIC section is also relatively higher in the LMF firm sample, suggesting that having a higher number of observations might change the results for other sections.

Fig. 2 Employment averages by SIC Section



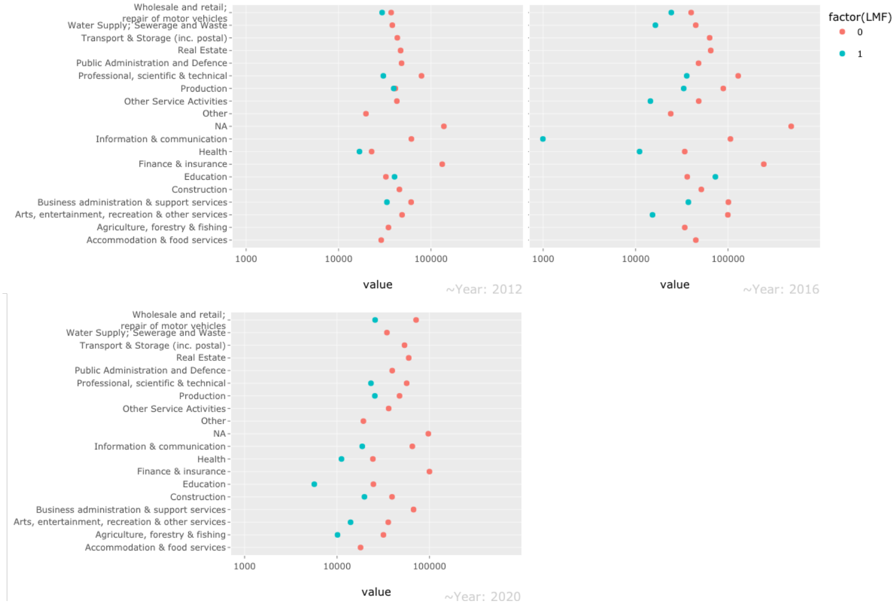
Median employment is comparable across KMFs and LMFs in 2012, with the median being 86 for KMFs and 79 for LMFs in this year. Same cannot be said about years 2016 and 2020: the median differs for the two type of firms. KMFs had a median employment of 85 in 2016 and 50 in 2020, the change likely being caused by the COVID-19 pandemic. LMFs, on the other hand, had median employment of 39 in 2016 and only 9 in 2020, meaning the median was significantly lower compared to KMFs.

Turning to wages, average remuneration was 37,801.22 in 2012 for KMFs and 32,360.7 for LMFs. The value dropped to 31,826.55 in KMFs and 19,679.26 in LMFs in 2020, respectively. This is a 15.8% change for KMFs and 32.2% change for LMFs, higher magnitude of change in LMFs being consistent with literature, as one would expect LMFs to adjust wages as opposed to employment in times of crisis.

Breaking average wages down by SIC section does not radically change the result. Estimates are shown in Figure 3 Average wage is consistently lower in LMFs for most SIC sections across the entire period. Exceptions include the education sector, for which the average wage was higher in LMFs for years 2012 and 2016, and the production sector, for which the average LMF wage was close to KMF wage in year 2012.

As mentioned previously, both samples are skewed towards large enterprises, with percentage of firms in the Small size bracket (6 to 11 employees) being as low as 0% for LMFs in 2012, and percentage of firms in the Large size bracket as high as 45 % for LMFs in the same year. For KMFs, firms of size Small comprised 10.21% and of size Large 44.14% of firms in year 2012, respectively.

Fig. 3 Wage averages by SIC Section



I also compute wage gaps for industries where data is available to find variation between the mean wage for LMFs and the mean wage for KMFs in a given year. Estimates are reported in table 11. I first report average wage gaps for all services industries, along with wage gaps for manufacturing, construction and agriculture, and then report wage gaps for specific services sectors. I also report wage gaps for firms where industry was not specified, and compute an average for all industries. It's important to note I do not distinguish between gaps in remuneration of employees and managers or directors, and this calculation only reports gaps in average remuneration across the firm. Data is only available for select industries and years, missing values are marked with *NA*.
For services, there is a negative wage gap, and it tends to increase over time, rising from -0.151 in 2012 to -0.435 in 2020, as the average wage was 14926 for LMFs and 29865 for KMFs in 2020, with the most pronounced discrepancy in *Education*. It's important to note that for *Education*, the wage gap is positive for 2012 and 2016, and quite large in 2016, with average wage being 72953 for LMFs and 31886 for KMFs in the data. This is attributed to the difference in the sample, not the underlying data.
For manufacturing the general dynamic is similar as for services, however, in 2012 the wage gap was positive, and the average wage was slightly higher for LMFs compared to KMFs. *Mining and quarrying* firms are not included in this calculation, as data is not available for LMFs. Average wage for manufacturing firms in the sample was 39533 for LMFs and 36383 for KMFs in 2012, and 25657 for LMFs, 35413 for KMFs in 2020. The total wage gap across all

industries also increased over the time period for which data is available, rising from -0.099 in 2012 to -0.269 in 2016, to -0.414 in 2020.

3.3.2 Results for the employment model

The results for the employment model are reported in table 6. I follow my hypotheses in interpreting results. H1 states that one should expect less elastic employment response to output price changes in LMFs compared to KMFs. I am not able to make claims with regards to the effect of changes in output prices on employment, as the estimate for the respective variable is not significant at a 5% level. The p-value of the estimate of log output price is 0.19. Based on this, I am also not able to establish differences in employment response to output price changes in LMFs as opposed to KMFs, as the interaction term is not meaningful while the estimate of the predictor variable is not significant. Moreover, the p-value of the interaction term is 0.9.

All other estimates in the model, however, are significant at least at a 5% significance level. As can be expected, the most important predictor of employment in a given year is employment in the preceding year. This is due to the fact that there is inertia involved in the way firms determine the employment level. Estimated coefficient for natural logarithm of lag employment is 0.86 with a p-value >0 and a standard error of 0.00. This means that for every unit of employment for the preceding year we would expect employment in current year to rise by 0.86 units, on average. The coefficient is 0.07 for the interaction with LMF status, with a p-value >0 and the standard error of 0.02. This means that the impact of log of lag employment on current employment is 0.07 units higher for LMFs, on average, a finding which confirms that LMFs are more conservative in their employment setting process. Other things equal, we would expect LMFs to not alter their employment level as drastically as KMFs.

I then analyse the effect of the wage level on employment. Estimated coefficient is -0.04 for log wage, with the standard error of 0.00 and the p-value >0. I interpret this as a single unit increase in log wage reducing the expected level of employment by 0.04, on average. This, again, is consistent with the literature, as one would expect to see lower employment levels when there are higher wages.

The estimate of the interaction term between LMF status and log wage is -0.09 with standard error of 0.04 and p-value of 0.02, significant at 2% level. The value of the coefficient implies that the negative effect of wage level on employment is even higher for LMFs, by 0.09 units, on average. This means one would expect to see lower employment in LMFs compared to KMFs where higher wages are present.

Finally, I interpret the differences in the way KMFs and LMFs adjusted employment during the COVID-19 outbreak in 2020. Estimated coefficient is -0.03 for the pandemic variable, with the standard error of 0.00 and a p-value >0. This means that, on average, other things equal, employment level fell by 0.03 units during the pandemic. The coefficient is 0.11 for the interaction term with LMF status, with the standard error of 0.04 and the p-value >0. This implies that the effect of pandemic on LMF employment is less pronounced, consistent with the fact that LMF employment tends to be more resilient to external shocks, as established by existing empirical research. In fact, estimated coefficient and the interaction term here taken together sum up to a positive value of 0.08, meaning one that employment has, on average, increased during the pandemic for LMFs.

I also fit the model for manufacturing and services firms separately. Estimates are reported in tables 7 and 8. Looking at the same model estimated for manufacturing only, with dummies for service industries excluded, many of the interaction terms with the LMF status are insignificant. One interaction term that is significant at 5% level is with the log wage, with the estimated coefficient of 0.09, standard error of 0.05, and p-value of 0.05, a result diametrically opposed to that of the general model. This estimate implies that for manufacturing firms expected employment is higher where there is a higher wage. This result could be due to a smaller sample compared to the general model.

For the model estimated only on service firms, excluding dummies for manufacturing industries, several interaction terms with LMF status are significant. Coefficient for the interaction with logarithm of lag employment is 0.1, standard error is 0.01, and p-value is >0. The effect is more pronounced for services compared to the general model. The result is similar for interaction with log wage and with the pandemic dummy, meaning the coefficient has the same sign as the one in the model that includes both firms in services and manufacturing, but is higher in magnitude. The coefficient for log wage is -0.18, standard error is 0.04, and p-value is >0. I. For pandemic, the coefficient is equal to 0.16, standard error to 0.05, and p-value is >0.

The value of adjusted R^2 is the same for all three models and equal to 0.97. For the model that includes firms in both services and manufacturing, F-statistic is 18489 on 22 and 121602 degrees of freedom, with p-value >0. I also compute the AIC value for this model, the estimate is 61712.25.

Table 6 Estimates for the Employment model

Term	Estimate	Std. Error	Statistic	P-value
(Intercept)	1.40	0.14	10.06	0.00
$\beta_{E,it}$	0.42	2.02	0.21	0.84
$\ln E_{it-1}$	0.86	0.00	223.64	0.00
$\ln E_{it-1} * C_i$	0.07	0.02	3.94	0.00
$\ln w_{it}$	-0.04	0.00	-14.29	0.00
$C_i * \ln w_{it}$	-0.09	0.04	-2.43	0.02
$\ln p_{it}$	-0.04	0.03	-1.33	0.19
$C_i * \ln p_{it}$	0.05	0.40	0.13	0.90
Pandemic	-0.03	0.00	-12.36	0.00
C_i*Pandemic	0.11	0.04	2.93	0.00

Cluster-robust standard errors are reported. Dummies for industry, size bracket and year were included in the model. The value of adjusted R^2 is 0.97.

3.3.3 Results for the wage model

The results for the wage model are reported in table 9. The coefficient for the log of relative output price is significant, with p-value >0, standard error of 0.03, and value of -0.09. This runs contrary to what one would expect to happen in practice based on existing research, as this coefficient implies that a single unit increase in relative output price reduces expected wage level by 0.09, on average. The result holds when the model is estimated using absolute output price instead of relative. Similar result holds when the year 2020 is left out of the data. Per H2, I expect wages in LMFs to be more sensitive to changes in relative output price compared to capitalist firms. I am not able to test this claim, as the interaction term of log relative output price with the LMF status is not significant at a 5%. The p-value is equal to 0.63.
The coefficients and standard errors for first and second log lags of wage are 0.59, 0.30 and 0.02, 0.01, respectively. The p-value for both estimates is >0. Both lags of wage explain a major share of the variation in the data. The interaction of log of first lag wage with LMF status is not significant at 5%. The coefficient is -0.15, the standard error is 0.09, and the p-value is 0.08. Interpreting the effect at an 8% significance level, the impact of log of first lag of wage is 0.15 units lower for LMFs compared to KMFs, meaning LMFs are more willing to adjust wages in response to changes in their environment, consistent with the literature.
Coefficient for the pandemic dummy is -0.02, with a standard error of 0.00 and p-value of 0.00. This can be interpreted as wage level falling by 0.02 units, on average, during the pandemic. The interaction term of the pandemic with LMF status is not significant at 5%, with the p-value being 0.16 and the coefficient being -0.09. Since this term is not significant, I'm also not able to test the H3, which suggested that decrease in wages would be less pronounced in KMFs compared to LMFs during the pandemic.
Same as with employment model, I fit the model separately for manufacturing and services firms. Estimates are reported in tables 10 and 11. For manufacturing, there are no pronounced differences in coefficients, although p-values fluctuate for different estimates. For example, p-value of log of output price is 0.06, meaning the result is not significant at a 5% level. On the other hand, p-value for the interaction term of LMF status with pandemic dummy is 0.09, meaning at a 5% level the result is still not significant, but it is significant at 9%. Interpreting this result, for manufacturing firms the magnitude of the effect of pandemic on wages was 0.05 units lower compared to the main effect, meaning wages were affected less in LMFs, a result that runs contrary to H3, which states there should be an effect in opposite direction.
For services only the magnitude of the coefficient for log of relative output price is much higher, -0.28, with standard error of 0.12, and p-value of 0.02. This means that for service firms, the negative effect of a rise in relative output price on wages is more pronounced than in the general model. The p-values in this model is different for the interaction term of log of first lag wage with the LMF status. The p-value is 0.14 for service firms, meaning the effect is not

significant at neither 5%, nor 8% level.
Adjusted R^2 is 0.77 for the model that includes both manufacturing and service firms, and the F-statistic is 199835 on 23 and 139623 degrees of freedom, with p-value >0. Adjusted R^2 is 0.69 for the model that only includes manufacturing firms, and 0.76 for the model that only includes service firms. The model that includes both manufacturing and services firms best explains the variation in the data.

Table 9 Estimates for the Wage model

Term	Estimate	Std. Error	Statistic	P-value
(Intercept)	1.60	0.14	11.09	0.00
$\beta_{w,it}$	0.82	1.82	0.45	0.65
$\ln w_{it-1}$	0.59	0.02	39.22	0.00
$\ln w_{it-2}$	0.30	0.01	23.29	0.00
$\ln w_{it-1} * C_i$	-0.15	0.09	-1.73	0.08
$\ln p_{it}$	-0.09	0.03	-3.23	0.00
$C_i * \ln p_{it}$	0.16	0.32	0.49	0.63
Pandemic	-0.02	0.00	-5.99	0.00
C_i*Pandemic	-0.09	0.06	-1.42	0.16

Cluster-robust standard errors are reported. Dummies for industry, size bracket and year were included in the model. The value of adjusted R^2 is 0.77.

3.3.4 Assumptions and limitations

One of the main limitations of this study is the fact that only LMFs registered with Companies House were included in the data set. This has a major impacts on the results, as firms registered under the Co-operative society legal form, the main legal form meant for worker cooperatives in the UK, were excluded from the data. This can be addressed in further research by collecting data from FCA, as discussed in section 3.1.3. This should also significantly increase the number of LMF firms in the data set, as in the original listing by Co-operatives UK only 1571 firms were registered with Companies House, as opposed to 7980 firms registered with FCA. Increasing the sample size for LMFs will not only provide more reliable results, but may enable comparisons of mean capital-labour ratios between LMFs and KMFs, which will allow to answer further research questions.
Another limitation of the study has to do with the fact that I do not distinguish between co-operative members and hired employees in LMFs. This has implications for wage and employment dynamics. Burdín (2012) [13] included this distinction, and was able to test for differenses in LMFs responses to output price shocks for members compared to non-members, and to confirm a negative wage-employment relationship for non-members. Although the data on the number of members and non-members is available for some firms in the data set used, it was not analysed in this study, and no data is available on individual wages of members and non-members, meaning wage comparison is

not possible.
Final critical limitation of the study is that I use annual data, and there are relatively few time periods available for analysis. If more granular data was available, e.g. monthly data, as in the study by Burdín, more robust panel data regression methods could be used, such as random or fixed within-effects estimation. If this was possible, it would have improved the quality and reliability of the results.

4 Discussion

The aim of this study was to compare how LMF and KMF firms adjust their employment and wages in response to changes in external conditions.
An example that offers a case study of a major external shock in the data is the COVID-19 pandemic. In the analysis, I don't find significant differences in how LMFs adjusted their wages in response to the pandemic, compared to KMFs. I do find differences in how LMFs adjusted their employment. The employment did not fall for LMFs during the pandemic, but has, on average, increased. This result is consistent with Burdín (2012) [13], in which the author studied the response of LMFs to the 2002 economic crisis in Uruguay. Although employment was negatively affected by the crisis in both LMFs and KMFs in this study, the magnitude of the impact was smaller for LMFs. Both LMFs and KMFs also adjusted their wage levels downwards in response to the crisis in the study, but there was no significant difference in the magnitude of adjustment, same as in this thesis.
Similar to Burdín, I find significant wage gaps between LMFs and KMFs in manufacturing and services, with LMFs, on average, having lower average wages compared to KMFs. The wage gap is growing over time, and increased in the years leading to 2020. Wage gap is less pronounced in this study compared to Burdín, approximately by the factor of 2-3 for manufacturing and services, meaning the magnitude of the discrepancy in wages is smaller in this data compared to data on Uruguayan firms assembled by Burdín. Although there are persistent wage gaps, only remuneration data was analysed in this thesis, and non-wage income, such as the share of profit that LMF members may receive as a return for their membership, was not included for in calculations. Incorporating it in the data in the future may alter results significantly.
To summarise, for UK in 2012-2020 and Uruguay in 1996-2005, employment in LMF firms tends to be, on average, more resilient to external shocks, such as financial crisis or pandemic, compared to KMF employment. On the other hand, average wages are lower in LMFs compared to KMFs, when non-wage income is not taken into account. There are no significant differences in how LMFs and KMFs adjust wages in crisis or pandemic, meaning LMF wage decrease is not of a higher magnitude compared to KMFs.

5 Conclusion

In this study, I analysed comparative behaviour of Labour-Managed Firms compared to their capitalist counterparts using data on firm performance in UK in years 2012-2020.

The data on LMF enterprise presented was not used in empirical research previously, and provides information on various financial indicators of such firms, such as assets, revenue, remuneration, and more. I use openly available data sets from Co-operatives UK and Companies House and collect, format and match the data to enable it to be used in econometric research.

Empirical approach in this thesis is designed to be compatible with other similar works that analyse data for different countries and time periods, to contribute to the body of knowledge on LMF behaviour and financial performance.

My hypotheses relate to the way in which LMFs and KMFs adjust their employment and wage levels in response to changes in output prices. I also study how both types of firms adjusted wages during the COVID-19 pandemic.

I don't find significant differences in either wage or employment adjustments with regards to relative output price, and don't find differences in the way firms adjusted wages in response to the pandemic.

I find significant differences in the way LMFs adjusted their employment during the COVID-19 pandemic. LMF employment in the pandemic increased, as opposed to KMF employment, which decreased.

Further studies could improve on this analysis by incorporating data on LMF firms registered with FCA into the data set, by introducing more granular financial data that would include information on monthly wages or individual wages of workers, and by distinguishing between members and non-members in the analysis of LMF wages and employment. Data on hours worked and working conditions, as well as the wage distribution, including the gender and racial wage gap, would allow to complete the portrait of LMFs and provide a definitive answer on whether the job quality in LMFs is, on average, better, compared to KMFs.

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6 Appendix

Table 12 Variable definitions for empirical models

Variable	Definition
$\ln w_{it}$	Average wage (in log form), calculated using a ratio of total remuneration over total employment; deflated using a consumer price index with 2015 as base year
$\ln E_{it}$	Employment measured as number of employees (in log form)
$\ln p_{it}$	Producer output price index (in log form), with values from UK PPI for manufacturing industries, SPPI for services industries
C_i	Dummy variable taking value 1 if the firm is LMF and 0 otherwise
$Micro_i$	Dummy variable taking value 1 if employment is less than 6 for firm i and 0 otherwise
$Small_i$	Dummy variable taking value 1 if employment is between 6 and 19 for firm i and 0 otherwise
$Medium_i$	Dummy variable taking value 1 if employment is between 20 and 100 for firm i and 0 otherwise
$Large_i$	Dummy variable taking value 1 if employment is more than 100 for firm i and 0 otherwise

Definitions are based on Burdín (2012) [13], industry dummies for each SIC section (sector) and year were included

Table 4 Descriptive statistics

Variable	2012 KMF	2012 LMF	2016 KMF	2016 LMF	2020 KMF	2020 LMF
Number of enterprises	31,024	20	42,519	28	69,232	25
Total employment	16,968,862	85,128	21,320,709	91,016	23,427,894	82,264
Avg. employment	546.96	4256.4	501.4396	3250.571	338.3969	3290.56
Minimum Median Maximum	1 86 648,254	2 79 81,900	1; 85 592,897	1 39 88,000	1 50 548,143	1 9 80,900
Employment std. error	38.171	4086.782	29.566	3,139.03	15.608	3,233.7861
Employees	100	X	100	X	100	X
Avg. wages	37,801.22	32,360.7	38,583.6	27,815.5	31,826.55	19,679.26
Wages standard error	107.809	3991.753	95.134	3782.812	80.924	3196.143
Manufact.	(21.78%)	25%	(18.92%)	21.43%	(13.71%)	24%
Services (ex. Retail)	(45.13%)	40%	(47.6%)	46.43%	(53.46%)	44%
Retail	(18.23%)	20%	(16.35%)	14.29%	(13.55%)	12%
Financial	(4.39%)	0%	(6.2%)	0%	(7.73%)	0%
Construction	(7.11%)	0%	(7.0%)	0%	(8.064%)	4%
Other sectors	(7.75%)	15%	(3.93%)	17.85%	(3.486%)	16%
Micro-enterprises	4.68%	20%	6.42%	25%	29.00%	40%
Small enterprises	10.21%	0%	10.5%	17.86%	9.42%	20%
Medium enterprises	40.96%	35%	38.6%	28.57%	28.76%	20%
Large enterprises	44.14%	45%	44.48%	28.57%	32.83%	20%

Table 5 Wage gaps

Variable	2012	2016	2020
Services	-0.151	-0.282	-0.435
Manufacturing	0.087	-0.118	-0.275
Construction	NA	NA	-0.393
Agriculture, Forestry and Fishing	NA	NA	-0.659
Administrative and Support Services	-0.164	-0.086	NA
Arts, Entertainment and Recreation	NA	-0.511	-0.364
Education	0.290	1.288	-0.725
Human Health and Social Work	-0.208	-0.497	-0.456
Information and Communication	NA	-0.981	-0.488
Professional, Scientific and Technical	-0.355	-0.223	-0.268
Water Supply; Sewerage and Waste	NA	-0.534	NA
Wholesale and Retail; Vehicle Repair	-0.319	-0.385	-0.307
Other Service Activities	NA	-0.605	NA
NA	-0.022	-0.302	-0.201
Total	-0.099	-0.269	-0.414

Table 7 Estimates for the Employment model, Manufacturing only

Term	Estimate	Std. Error	Statistic	P-value
(Intercept)	0.86	0.28	3.04	0.00
$\beta_{E,it}$	1.17	2.30	0.51	0.61
$\ln E_{it-1}$	0.90	0.01	97.24	0.00
$\ln E_{it-1} * C_i$	-0.02	0.02	-1.03	0.30
$\ln w_{it}$	-0.07	0.01	-4.55	0.00
$C_i * \ln w_{it}$	0.09	0.05	2.00	0.05
$\ln p_{it}$	0.08	0.04	2.16	0.03
$C_i * \ln p_{it}$	-0.42	0.45	-0.95	0.34
Pandemic	-0.01	0.01	-2.72	0.01
C_i*Pandemic	0.02	0.03	0.68	0.50

Cluster-robust standard errors are reported. Dummies for industry, size bracket and year were included in the model. The value of adjusted R^2 is 0.97.

Table 8 Estimates for the Employment model, Services only

Term	Estimate	Std. Error	Statistic	P-value
(Intercept)	1.72	0.33	5.15	0.00
$\beta_{E,it}$	4.53	4.61	0.98	0.33
$\ln E_{it-1}$	0.85	0.00	175.79	0.00
$\ln E_{it-1} * C_i$	0.10	0.01	8.28	0.00
$\ln w_{it}$	-0.04	0.00	-11.88	0.00
$C_i * \ln w_{it}$	-0.18	0.04	-4.67	0.00
$\ln p_{it}$	-0.09	0.07	-1.30	0.19
$C_i * \ln p_{it}$	-0.67	0.93	-0.72	0.47
Pandemic	-0.03	0.00	-9.02	0.00
C_i*Pandemic	0.16	0.05	2.85	0.00

Cluster-robust standard errors are reported. Dummies for industry, size bracket and year were included in the model. The value of adjusted R^2 is 0.97.

Table 10 Estimates for the Wage model, Manufacturing only

Term	Estimate	Std. Error	Statistic	P-value
(Intercept)	1.64	0.25	6.46	0.00
$\beta_{w,it}$	0.85	2.96	0.29	0.78
$\ln w_{it-1}$	0.54	0.05	9.99	0.00
$\ln w_{it-2}$	0.34	0.05	7.35	0.00
$\ln p_{it}$	-0.08	0.04	-1.85	0.06
Pandemic	-0.02	0.01	-2.51	0.01
$\ln w_{it-1} * C_i$	0.03	0.04	0.72	0.47
$C_i * \ln p_{it}$	-0.23	0.68	-0.35	0.73
C_i*Pandemic	-0.05	0.03	-1.68	0.09

Cluster-robust standard errors are reported. Dummies for industry, size bracket and year were included in the model. The value of adjusted R^2 is 0.69.

Table 11 Estimates for the Wage model, Services only

Term	Estimate	Std. Error	Statistic	P-value
(Intercept)	2.56	0.57	4.54	0.00
$\beta_{w,it}$	3.77	2.98	1.27	0.21
$\ln w_{it-1}$	0.57	0.02	26.33	0.00
$\ln w_{it-2}$	0.31	0.02	16.29	0.00
$\ln p_{it}$	-0.28	0.12	-2.38	0.02
Pandemic	-0.02	0.01	-3.37	0.00
$\ln w_{it-1} * C_i$	0.06	0.04	1.47	0.14
$C_i * \ln p_{it}$	-0.95	0.69	-1.37	0.17
C_i*Pandemic	0.08	0.09	0.91	0.36

Cluster-robust standard errors are reported. Dummies for industry, size bracket and year were included in the model. The value of adjusted R^2 is 0.76.