Output, Investment and Capacity: An Empirical Investigation using Firm-Level Business-Survey Data in the United Kingdom

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Abstract

This thesis uses firm-level survey data to examine the decision-making of firms in order to gain greater insight into macrodynamics.

Chapter 2 examines the questions posed, the sample frame (i.e. details on the number and participation rates of respondents) and the characteristics of the firm participants of the Confederation of British Industry's (CBI) suite of business surveys. This dataset of firm-level survey responses is then matched to two external company accounts datasets (the Bureau van Dijk FAME dataset and the Office of National Statistics (ONS) Inter-Departmental Business Register (IDBR), including various ONS business surveys). Matching to external data sources often requires decisions to be made on how the matching should be conducted. Matching the CBI data to the IDBR yields a set of multiple matches when propensity-score matching is unable to select a definite match. Rather than dropping these firms from the sample, this chapter develops a decision rule to select a unique match from this set of multiple matches. Match results are around 50% when matching the CBI dataset with the Bureau van Dijk FAME dataset and around 90% when matched with the IDBR. However, match rates with the various ONS business surveys are lower than the corresponding match rates with the Bureau van Dijk FAME dataset (and in some cases far lower). Match rates are also reported for variation by geography, size and time-period. The matched dataset is then used in an illustrative exercise to examine the directional accuracy of firm output and employment forecasts. The results indicate the output and employment forecasts of firms in the manufacturing and mining and distributive trades sectors have value. However, this is not the case in either the service or financial services sector.

Chapter 3 introduces the new and novel meta-modelling quantification approach, which is used to produce quantitative industry-level measures of expected output growth, output disagreement and output uncertainty in the UK (using firm-level survey responses in the CBI dataset). This new quantification strategy provides more reliable estimates of expected output growth and output uncertainty compared to existing techniques such as the simple balance statistic (or the Anderson-Pesaran regression approach). These new quantified series are employed alongside actual output growth data in an analysis of the source of innovations and propagation mechanisms underlying output dynamics. These interactions are complex and out-of-line with those suggested by simple models embodying rational expectations. In addition, using a Beveridge-Nelson trends decomposition, this chapter shows there is a role for output uncertainty and output disagreement shocks in influencing business cycle dynamics - with these having relatively substantial effects of up to 4% in different sectors during the Great Financial Crisis (GFC), the sovereign debt crisis and the Brexit negotiations.

Chapter 4 extends the classic Abel (1981) paper to introduce capacity utilisation into a dynamic model with adjustment costs describing investment and hiring decisions of the firm. It provides an analytical solution for the theoretical model and then uses survey data from the CBI Industrial Trends Survey to test the model empirically. The results show that firms adjust their capital stock around a long-run equilibrium determined by sales over time. However, the speed of this adjustment depends on whether the model accounts for a capacity error correction term. Specifically, models which do not include a capacity error correction term overestimate the error correcting behaviour of firms, and imply a quicker adjustment speed of capital to its long-run equilibrium value. In other words, excluding capacity dynamics from an accelerator model of investment underestimates the time it takes capital to return to its long-run equilibrium value - providing an explanation for sluggish investment following recessionary periods.

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Chapter 1

Introduction

1.1 Overview of Thesis

The purpose of this thesis is to examine the insights which can be obtained from firm-level datasets on macroeconomic dynamics. Macrodynamics are complicated when considered at the economy-wide level, arising as the outcome of many interrelated decisions at the level of the firm (each faced with idiosyncratic demand and supply shocks and adjustment costs). Using the Confederation of British Industry (CBI) suite of business surveys this thesis provides an insight into the decision-making of firms - a central element of which is the role of expectations, as firms anticipate and respond to future conditions and the uncertainties surrounding these. A key contribution of this thesis is the valuable information contained in firm-level surveys and how this can be analysed to provide an insight into firm-decision making (and the wider economy as a whole).

Chapter 2 discusses how the CBI dataset can be matched to external company accounts data so firm-level survey responses (providing information on firm decision-making) is matched with actual outcomes (i.e. the decision the firm actually made). As an example of the benefits of matching these data sources, this chapter also tests the directional accuracy of firm output and employment forecasts using the survey-based ex-ante forecast and the corresponding actual outcome from company accounts. Chapter 3 shows how an industry-level quantified expected output growth, output disagreement and output uncertainty series can be constructed and how these quantified series can be used in a straightforward Vector Autoregression (VAR) model (along with actual output growth from official statistics) to analyse the dynamic interactions between these key macroeconomic variables. The results of this analysis can then be used to examine the impact of output uncertainty shocks actually observed on the UK economy (specifically, in the aftermath of the Great Financial Crisis (GFC)). Chapter 4 shows how the adjustment of capital stock back to its long-run equilibrium is slower when technology is putty-clay (i.e. the capital stock is fixed in the short-run) rather than putty-putty (i.e. when firms can freely adjust their capital stock). The assumption of putty-clay technology is more reasonable and implies firms are forced to adjust their rate of capacity utilisation in the short-run in response to demand. This slower adjustment of capital (when firms adjust their rate of capacity utilisation) provides an explanation for the low levels of investment in the aftermath of the GFC.

The remainder of this chapter is as follows: Section 1.2, Section 1.3 and Section 1.4 provide a more detailed (but brief synopsis of) Chapter 2, Chapter 3 and Chapter 4 (respectively).

1.2 The Second Chapter: An Exercise in Data Matching and Accuracy of Directional Forecasts

Chapter 2 has three aims. First, it provides an overview of the primary data source for this thesis - the CBI suite of business surveys, which covers the manufacturing and mining sector, service sector, distributive trades sector and financial services sector. Second, it examines how firm-level survey responses are matched to company accounts data - specifically to the Bureau van Dijk FAME dataset and the Office of National Statistics (ONS) Inter-Departmental Business Register (IDBR), including various ONS business surveys. Third, using the firm-level ex-ante survey forecasts and corresponding company accounts outcome data it tests the directional accuracy of output and employment forecasts.

1.2.1 An Overview of the Dataset

The CBI dataset consists of monthly firm-level qualitative survey responses to four individual business surveys covering the manufacturing and mining sector (from the Industrial Trends Survey (ITS)), the service sector (from the Service Sector Survey (SSS)), the distributive trades sector (from the Distributive Trades Survey (DTS)) and the financial services sector (from the Financial Services Survey (FSS)). The longest running survey (the ITS) started in 1958, while the shortest running survey (the SSS) started in 1998 - thus the CBI dataset yields a continuous set of survey responses since just before the turn of the century. Previous literature has focused primarily on survey responses from the ITS alone. In contrast, this chapter (and the thesis more generally) also utilises the data contained in the remaining surveys of the CBI dataset.

The surveys are a mix of industry-specific questions (for example, only the ITS asks detailed questions related to capacity, inventories or order book) and generic questions (including questions related to business confidence, volume of business (or output), investment and investment constraints). Furthermore, these economic variables are measured both retrospectively and in expectation - providing a rich source of real-time information on the state of the economy. Thus, the CBI dataset provides a detailed and timely description of the state of the economy over many years and at a relatively high frequency (as the questions posed relate to a wide range of economic magnitudes, the surveys have been conducted over a significant time frame and are conducted monthly). In addition, the panel structure of the CBI dataset (including both a substantial cross-section of firms over a significant time-horizon) allows individual firm responses to be tracked over time. This chapter discusses the scope of each survey (i.e. the questions posed to survey participants), the sample frame (including the timespan of the survey, the number of firm participants and the continuity of firm participation) and the characteristics of the firm participants (including size, industrial classification and location of firm participants).

1.2.2 Matching Survey Data to Company Accounts Data

The matching exercise in Chapter 2 involves matching the CBI dataset to the Bureau van Dijk FAME dataset and the IDBR. This matching exercise creates a new, richer dataset where new insights can be gained at the microeconomic level. For example, the relatively detailed explanations of the thinking behind firms' investment plans (from the CBI dataset) can be matched with accounting information available in company accounts. Moreover, the decisions about investment can be linked to qualitative responses in the survey on incentives and constraints on investment, and to other measures of activity such as production, sales, inventories and capacity utilisation.

Matching can only be achieved through the existence and uniqueness of a matching key, which must be common to all datasets to allow for an accurate match of firm-level data. For matching to the Bureau van Dijk FAME dataset (implemented by Bureau van Dijk themselves via their online database) the firm name constitutes the matching key. Matching is achieved using a modified trigram matching algorithm (a type of vectorial decomposition). Firm name, address and postcode is the matching key for matching to the IDBR. Matching to the IDBR constitutes the first step[1] in matching the CBI dataset to the Annual Business Survey (ABS), the Quarterly acquisitions and disposals of Capital Assets Survey (QCAS) and Monthly Business Survey (MBS)[2]. Matching to the IDBR involves using a propensity-score matching approach which yields a set of definite matches (i.e. where a firm in the CBI dataset is matched to only one Reporting Unit reference

[1]After matching to the IDBR, firm-level responses in the CBI dataset can be easily linked with ONS business surveys.

[2]As well as the relevant precursors to these surveys.

(RUref)[3] in the IDBR), a set of multiple matches (i.e. where a firm in the CBI dataset is matched to more than RUref in the IDBR) and a set of no matches (i.e. where a firm in the CBI dataset is not matched to any RUref in the IDBR).

A key contribution of this chapter is the derivation of a methodology which identifies a unique match among the set of multiple matches. First, construct a "survey score" to indicate the presence in the ABS, QCAS and MBS of each RUref in each period. The survey score is calculated as the fraction of surveys a RUref has appeared in over a considerable period of time with a value of one (zero) indicating it is present (absent) in all surveys in the period used. The scores are then averaged across the ABS, QCAS and MBS (as all are equally important to the analysis). Second, match data on employment size (from 2019Q4 snapshot of the IDBR) to the set of RUref multiple matches. Third, apply the allocation rule to define the unique match. There are three consecutive steps to this allocation rule. Step one, since the same RUref can appear multiple times for the same company (as it matches to different parts of the same entity on the IDBR) de-duplicate the list - and if only one RUref is left, use that one. Step two, if there are still multiple matches then select the RUref with the highest survey score assuming no other option is within 5%. For those that are within 5%, if only one of them appears at least once in all the surveys (ABS, MBS and QCAS) - select it. For those that are within 5%, and none are in all the surveys (ABS, MBS and QCAS), select the one with largest employment. Step three, if the survey score is zero then choose the RUref with the largest employment.

Using these matching techniques, the match rate between the CBI dataset and Bureau van Dijk FAME dataset is 49.8% (with a similar match rate for each individual CBI survey). This match rate considerably improves to 72.3% for large firms, but remains modest (41.7%) for micro, small and medium firms[4]. The match rate between the CBI dataset and the IDBR is significantly higher at 89.5%. Nor is there any discrepancy between match rates based on firm size. Using this matched IDBR-CBI dataset, the match rates with the ABS, QCAS and MBS are good (but smaller than the Bureau van Dijk FAME match rates)[5]. Thus, this data matching exercise yields a new (unique) dataset (containing both qualitative survey responses with company accounts data) with good match rates of firms across the UK.

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[3] A RUref is a statistical unit, agreed between ONS and the business as the appropriate level for survey responses.

[4] Large firms are defined as having 250 or more employees while micro, small and medium firms have fewer than 250 employees.

[5] Only the FSS has consistently poor match rates with the ABS, QCAS and MBS. The only other poor match rate is between the DTS and MBS.

1.2.3 Testing the Directional Accuracy of Firm Forecasts

The new matched CBI and company accounts dataset consists of (among other variables) firm-level ex-ante survey forecasts and corresponding (quantitative) actual outcome data. This data mix is a necessary prerequisite for a rationality criterion using the mean of the firm's subjective density forecast, which is subsequently used to form disaggregate non-parametric tests measuring the directional accuracy of forecasts. This criterion (first proposed by Das et al. (1999)) treats the firm-level ex-ante survey forecast as the mean of the firm's subjective density forecast. In other words, firms act as if minimising their squared forecast errors. This criterion compares the ex-ante survey forecast with the corresponding (quantitative) outcome data from company accounts. The answer bins for the ex-ante survey forecast are "down", "same" and "up". Firms report their ex-ante survey forecast is "down" ("up") when their corresponding latent, quantitative firm-level expectation falls below (rises above) a lower (upper) answer bin threshold. Similarly, firms report their ex-ante survey forecast is "same" when their corresponding latent, quantitative firm-level expectation falls between the lower and upper answer bin thresholds. Firms satisfy the rationality criterion if the actual quantitative outcome is drawn from the same distribution on which the ex-ante forecast is based. Specifically, firms which have selected "down", "same" or "up" are rational if the mean of the distribution of (quantitative) outcomes is in answer bin "down", "same" or "up" (respectively). The relative forecasting skill of firms is measured by comparing the number of rational forecasts (corrected for random guessing) with the perfect forecast counterfactual. This is the Hanssen and Kuipers discriminant, and it indicates whether firm forecasts are less than, equal to or better than random in forecasting. A Pearson-Chi Square test formally tests the directional accuracy of forecasts, by testing if there is an association between the firm's ex-ante survey forecasts and the corresponding classification of the quantitative outcome.

In addition to requiring data on the ex-ante survey forecasts and actual outcomes, the rationality criterion using the mean of the firm's subjective density forecast requires quantitative data on the lower and upper answer bin thresholds. These answer bin thresholds are often unobserved, vary over time, are different for each firm and are (typically) unavailable from survey data. Lacking reliable quantitative data on these answer bin thresholds, firms cannot be classified based on the rationality criterion using the mean of the firm's subjective density forecast. As a result, previous studies have had to rely on testing the implications of this rationality criterion. In contrast, this chapter uses firm survey responses to the CBI's Answering Practices Survey (APS) to construct reliable, quantitative measures of the upper and lower answer bin thresholds. The APS is a survey for participating firms in the CBI suite of business surveys, where respondents answer a series of questions regarding how they complete their designated survey - in particular, by indicating how they interpret the survey questions and potential answers.

The disaggregate rationality criterion using the mean of the firm's subjective density forecast test is applied to output and numbers employed. The corresponding Pearson-Chi Square test results indicate the output and employment forecasts of firms in the manufacturing and mining and distributive trades sectors have value. However, this is not the case in either the service or financial services sector.

1.3 The Third Chapter: Quantifying Output Uncertainty and it's Actual Impact on the UK Economy

The purpose of Chapter 3 is twofold. First, it presents a new technique to quantify a qualitative time series. This technique is then applied to the CBI dataset to construct industry-level measures of expected output growth, output disagreement and output uncertainty. Second, using the newly quantified series it shows the impact of actual output uncertainty shocks on the UK economy in the immediate aftermath of the Great Financial Crisis (GFC).

1.3.1 Quantifying Survey Responses

Firm-level survey data (such as the CBI dataset) contains a wealth of information (usually at high frequency and covering a large range of economic variables), providing a key insight into the state of the economy at any point in time - usually with a shorter time lag than official statistics. A potential reservation to the use of this data is that it is qualitative - meaning firms do not provide explicit expectation or realisation data on output (say), instead providing answers "up", "same" or "down". If these qualitative responses can be reliably and accurately translated into a quantified series, then a wealth of additional data is available to both researchers and policymakers[6]. Standard quantification techniques of a qualitative series include the simple balance statistic, the Carlson-Parkin probability approach and the Anderson-Pesaran regression approach. The simple balance statistic quantifies a qualitative series by subtracting the proportion of firms reporting a decrease in the variable of interest from the proportion of firms reporting an increase (Pesaran, 1987). The Carlson-Parkin probability approach assumes each firm possess the same subjective probability distribution over a particular variable, and only when

[6] Quantification necessarily involves aggregation of firm-level survey responses. For example, qualitative firm-level survey responses can be translated into a quantified industry-level series.

this variable exceeds a certain threshold value will firms report an expected change in this variable (Pesaran, 1987). The Anderson-Pesaran regression approach makes no assumptions regarding the firm's subjective probability distribution - rather it enhances the simple balance statistic by exploiting the relationship between actual changes in the variable (from official statistics) and realisations perceived by the firms (Pesaran, 1987). According to Pesaran (1987) such a regression serves to identify a relationship between the official statistics and survey results, rather than expounding a causal response[7].

1.3.1.1 Existing Quantification Strategies

Given that subjective survey responses are being translated into an aggregate quantified series, the choice of quantification strategy is arbitrary (Pesaran, 1987). However, existing techniques include restrictive assumptions. The simple balance statistic assumes constant and symmetric quantification of the qualitative series. Firm survey responses "up" and "down" are always quantified (through the whole sample, irrespective of economic conditions) as +1 and -1, respectively. This implies the average percentage increase in output for firms experiencing a rise in their output equals (in absolute terms) the average percentage decrease of output for firms experiencing a fall in their output - and remain unchanged throughout the sample. In reality, during so-called "good times" it is expected that the quantification of "up" should be larger than the quantification of "down" - with the converse also being true. Applying the simple balance statistic approach to qualitative measures of output in the CBI dataset and comparing it to official statistics demonstrates that the assumption of constant and symmetric quantification fails to account for structural change. While the Anderson-Pesaran regression approach relaxes the symmetric quantification assumption ("up" and "down" are quantified as $+\alpha$ and $-\beta$), it still assumes constant quantification - and thus still doesn't properly account for structural change[8].

The Carlson-Parkin probability approach also relies on unrealistic (and untestable) assumptions. First, it assumes all firms possess the same subjective probability distribution over a variable - the choice of which is arbitrary and not based on evidence contained in firm survey responses. Second, the Carlson-Parkin probability approach is a threshold-crossing model with an unobservable threshold that requires estimation[9]. Not only is this

[7] For each of these approaches the respective corresponding second moments can be utilised to obtain a measure of disagreement.

[8] Estimates of $+\alpha$ and $-\beta$ are obtained from a regression of the aggregate actual series (from official statistics) on the proportion of firms answering "up" and "down" to a retrospective question on the variable from the survey (respectively). Thus the Anderson-Pesaran regression approach requires both a retrospective and expectation question in the survey to construct an industry-level quantified expectation series.

[9] See Pesaran (1987) for a criticism of these threshold estimation techniques.

an unrealistic assumption but when using either a normal or logistic distribution can provide misleading first moment estimates when firms switch from "same" to either "up" or "down" in their response categories (Pesaran, 1987). While the probability approach can be amended to allow the threshold to be non-constant and non-symmetric, this still leaves the issue of accurately estimating an unobserved threshold. Third, the Carlson-Parkin probability approach does not work if the proportion of firms reporting either up or down is zero (Pesaran, 1987).

1.3.1.2 The Novel Meta-Modelling Quantification Approach

A key contribution of Chapter 3 to the existing literature is the development of a non-constant and non-symmetric quantification technique that does not rely on untestable assumptions or arbitrary decisions by the researcher. This meta-modelling quantification approach (following Lee et al. (2015) and Aristidou et al. (2019), which is based on the Bayesian Model-Averaging formula in Hoeting et al. (1999)) provides a relatively straightforward means of translating firm-level qualitative survey responses into an industry-level quantitative series, while taking into account the changing nature of the relationship between survey responses and outcomes. This meta-modelling quantification approach extends the Anderson-Pesaran regression approach by using a set of rolling regressions of varying window size τ (yielding a set of estimates of $+\alpha_\tau$ and $-\beta_\tau$), but at each point in time the data chooses the appropriate sample window (using a series of weights). Weights (updated each quarter) are applied to each model of rolling window size τ and are sequentially allocated downwards to models with smaller values of τ which outperform models with larger values of τ (based on the results of the predictive failure test of structural stability). Thus, weights are dynamically selected each period based on the existence of structural breaks. Periods of stability see weights shifted to models with larger values of τ, while weights are cascaded to models with smaller values of τ following structural breaks.

This approach balances the advantages of longer samples versus short samples and removes the researchers ability to arbitrarily choose a rolling window size for quantification (as no value of τ is a priori preferential to any other). Combining these weights with $+\alpha_\tau$ and $-\beta_\tau$ provide a reliable quantification of firm-level survey responses. Applying the meta-modelling quantification approach to obtain an industry-level quantified expected output growth measure from the CBI dataset and comparing it to official statistics demonstrates this techniques superiority to the simple balance statistic. While Chapter 3 applies the meta-modelling quantification approach to output data, it can easily be applied to other qualitative variables (so long as there is both a forward and backward looking question on the variable of interest).

These quantification techniques are also applied to constructing industry-level measures of output disagreement and output uncertainty. Output disagreement is defined as the cross-section dispersion of firm survey responses (constructed using the meta-modelling quantification approach). Following the construction of an expected output growth series using the meta-modelling quantification approach, the ARCH estimate of the industry-level expectation error (the difference between expected and actual output growth) yields a survey-based output uncertainty measure. This output uncertainty measure is not only countercyclical with actual output growth in each industrial sector (a key attribute found in existing literature), but is also derived directly from the views of market participants and captures the uncertainty of market participants as they make their decisions (and not after).

1.3.2 The Actual Impact of Observed Output Uncertainty Shocks

A four system cointegrating VAR (consisting of the quantified industry-level measure of output uncertainty, output disagreement and expected output growth as well as actual output growth from official statistics) is constructed to analyse the source of innovations and propagation mechanisms underlying output dynamics. A causal ordering of the shocks is imposed through a Choleski decomposition. Output decisions are made against a backdrop of uncertainty, so that output uncertainty and output disagreement are determined prior to actual and expected output growth. Similarly, current decisions are based on expectations of the future so that output uncertainty precedes output disagreement and expected output growth precedes actual output growth. Consistent with previous literature, an uncertainty shock has a negative impact on expected and actual output (in levels). Both expected and actual output (for each industrial sector) decrease to a permanently lower long-run level circa 0.2% to 0.6% below its initial value. Following a one standard deviation expected output shock, actual output increases to a permanently higher long-run value which is circa 1.2% higher than its pre-shock value in the manufacturing and mining and service sectors and circa 2.6% higher in the distributive trades sector. In each sector, both expected and actual output converge to the same long-run value. However, convergence is slow and non-monotonic - in contrast to full-information rational expectations (where the response of actual output would mirror the expected output response after one quarter). Following a one standard deviation actual output shock, expected output increases to a permanently higher value circa 0.7%, 1% and 1.8% higher than their pre-shock values in the manufacturing and mining, service and distributive trades sectors (respectively).

While these impulse responses are useful in describing the dynamics of the estimated model, the implications for the macroeconomy are better captured using a Beveridge-Nelson trend. The Beveridge-Nelson trend is the steady-state output level and reflects the size of the shocks actually observed in the data as well as the infinite horizon effects captured by the impulse responses. Thus, the Beveridge-Nelson decomposition is used to examine the effects of actually observed output uncertainty shocks in the UK economy (using the survey-based measure of output uncertainty, quantified using the meta-modelling quantification approach). For example, shocks to output uncertainty and output disagreement caused trend output in the manufacturing and mining sector to be circa 2.5% to 4.5% lower than it would have been in the absence of shocks through 2008-2012, and circa 1% to 2% lower at the end of the sample. Comparably large effects for output uncertainty and output disagreement are observed in the service and distributive trades sectors.

1.4 The Fourth Chapter: Including Capacity Utilisation in an Investment Equation

The purpose of this chapter is specify and estimate a firm-level investment equation under the assumption of putty-clay technology, in contrast to the standard assumption of putty-putty technology. This frames an investment specification in an environment where firms face fixed factors of production in the short-run, and are therefore forced to use their rate of capacity utilisation as a short-run buffer.

1.4.1 Issues with Putty-Putty Technology

The key motivation for this exercise are the unrealistic (and unfounded) implications which underpin the assumption of putty-putty technology. With putty-putty technology factors of production can be adjusted at any point in time, can be easily reoriented to any task at hand and no factor of production is under-utilised (as any under-utilised resource would be reoriented to reduce variable costs). In reality, factors of production can be fixed in the short-run - contradicting the implications of the putty-putty technology assumption. First, there is a time lag to adjusting stocks of capital and labour (for example, it takes time to install new capital and train new employees). Second, capital (and to some extent labour) is task-specific and cannot easily be reoriented in a short period of time to accomplish new tasks. Third, data from the ITS indicates that firms do have under-utilised (or idle) factors of production - with 59.19% of survey responses stating firms are working below a satisfactory full rate of operation. Therefore, estimating a firm-level investment equation under the putty-putty technology assumption can give rise to misleading results as it overestimates the ability of firms to adjust their capital stock in the short-run. In reality, these stocks are fixed in the short-run (as with putty-clay technology) and firms adjust their rate of capacity utilisation (and not stocks of capital or labour) in the short-run in response to demand. The primary contribution of Chapter 4 is to specify and estimate an investment equation with putty-clay technology using a direct measure of firm-level capacity utilisation from the ITS.

1.4.2 The Abel (1981) Framework

Abel (1981) provides a framework for specifying a firm-level investment equation in a putty-clay environment by including a capacity utilisation variable in a firms production function (along with the standard capital and labour stock). This is achieved by interacting the capacity utilisation variable with the labour stock in the firm production function. This reflects that increased capacity utilisation requires an increased use of the labour stock (for example through overtime, zero-hour contracts or agency work). In order to use machines more intensively increased use of the labour stock is required. The firm optimisation problem is to maximise the present value of its flow of funds with decision variables capacity utilisation, investment in capital stock and investment in labour stock - yielding the optimal rate of capacity utilisation as an increasing (decreasing) function of the capital-effective labour ratio (real wage rate).

The steady-state (or long-run value) for capital remains the same as with putty-putty technology (i.e. in the long-run capital is still proportional to sales). In the long-run capacity is proportional to the user cost of labour. Linearising the Abel (1981) framework around the steady-state values for capital and capacity yields a firm-level investment specification with putty-clay technology. This investment specification contains a capital error correction term (like its putty-putty counterpart), which is the degree of the breakdown in the long-run relationship between capital and its long-run value (sales). In other words, this capital error correction term measures the correction of the disequilibrium each period. In the short-run, capital can wander from its long-run equilibrium path - but in the long-run the capital error correction term will pull it back. However in contrast to the putty-putty investment specification, the putty-clay specification also contains a capacity error correction term (which captures the previous period's deviation of capacity from its long-run equilibrium value). While the capital error correction term is expected to be negative (indicating that future investment increases when capital falls below its desirable long-run level), the capacity error correction term is expected to be positive. In the short-run (with fixed capital and labour stock) firms increase their rate of capacity utilisation (i.e. intensify their use of capital and labour stock) in response to an increase in demand. This is only a short-run solution (as capital wears quicker, overtime rates for labour are expensive). Thus, in the long-run firms invest more (to augment their capital and labour stock) to meet demand in a more sustainable way. There is still an adjustment of capital to its long-run equilibrium value - but it is now expected to be slower than in the putty-putty environment (as firms now alter their rate of capacity utilisation).

1.4.3 Results

Firm-level investment equations with both putty-putty and putty-clay technology are estimated using system GMM. As expected, the capital error correction term is negative for both specifications. As expected, the error correcting behaviour in a putty-putty environment is greater than in a putty-clay environment. In other words, when estimating an investment equation with putty-clay technology the extent to which firms correct the imbalance between capital stock and its long-run equilibrium value each period is now reduced. As expected, the capacity error correction term is both positive and statistically significant. Excluding the capacity error correction term from the firm-level investment equation overestimates the extent to which firms respond to disequilibrium between actual and desired capital, as it ignores the ability of firms to adjust their utilisation of capital. These results are robust to the inclusion of a series of firm-level investment constraints (such as uncertainty, insufficient finance and poor proposed return on investment). These results provide an explanation for the prolonged lack of investment in the UK economy post-GFC. For example, after a negative system-wide shock (where there is both a simultaneous capital and capacity utilisation shock) there is a distinct lack of investment in capital stock as firms instead increase their rate of capacity utilisation. Similarly, following a (permanent) negative exogenous sales shock capital steadily falls to a permanently lower level in the long-run (equal to the now permanently lower level of sales) with both putty-putty and putty-clay technology. However, the speed of this adjustment differs - in a putty-putty environment adjustment is quicker due to the faster error-correcting process. Thus, in the immediate aftermath of the GFC capital began a long and slow adjustment towards a permanently lower level - an adjustment that is even slower if firms face fixed factors of production in the short-run and instead adjust their rate of capacity utilisation.

Chapter 2

Data-Matching and the Directional Accuracy of Firm Forecasts: A Study using the Confederation of British Industry (CBI) Suite of Business Surveys

2.1 Introduction

This chapter provides an overview of the data sample, structure and uses of the Confederation of British Industry (CBI) suite of business surveys[1]. There are four main surveys in the suite, comprising the long running Industrial Trends Survey (ITS), the Service Sector Survey (SSS), the Distributive Trades Survey (DTS) and the Financial Services Survey (FSS). The questions differ to reflect the nature of the business that is conducted in each sector. The surveys gather information from thousands of firms on various economic outcomes, both retrospectively and in expectation, and provide a rich source of real-time information on the state of the economy.

Data from the CBI suite of business surveys has previously been used in academic studies. Pesaran (1984, 1987) uses the CBI dataset as a testbed of quantification techniques before examining the ability of derived (price) inflation expectations to forecast actual inflation. Lee (1994) also creates a quantified (price and unit cost) inflation expectation series with the aim of testing the rational expectations hypothesis. Lee and Shields (2007) enhance

[1]Lee et al. (2020a) and Mahony and Martin (2022) are based on work contained in this chapter.

the standard quantification technique by removing discretisation errors. Lui et al. (2011a, 2011b) compare the qualitative survey responses of the CBI suite of business surveys with the corresponding quantitative responses to the Office of National Statistics (ONS) Monthly Production Inquiry to test the validity of firm responses in the CBI dataset and examine the rationality of expectation formation[2]. Boneva et al. (2020) utilise the CBI dataset to examine the influences on firm-level expectations. Mitchell et al. (2002, 2013) and Mitchell et al. (2004, 2007) use the CBI dataset to update the standard Carlson-Parkin quantification approach with time-varying thresholds affecting firm responses (as opposed to the standard time invariant thresholds) to derive an expected manufacturing output growth series and a second moment series of investment in buildings, plant and machinery. Temple et al. (2001), Driver et al. (2003), Driver et al. (2004, 2007) and Driver et al. (2005a, 2005b, 2006, 2008) construct a quantified uncertainty series and examine its impact on firm-level investment, test the real options theory of uncertainty and compare cross-section and time series measures of uncertainty. Driver and Urga (2004) construct and compare quantified expectation series for investment (plant and machinery), output, employment, export deliveries, domestic prices and unit costs.

Despite this extensive literature there are still new insights to be gained from the CBI dataset. The survey questions relate to a wide range of economic magnitudes and given that the surveys have been conducted for some time and on a monthly basis, means that they provide a detailed and timely description of the state of the economy over many years and at a relatively high frequency. For example, new insights can be gained at the microeconomic level if the firms' survey responses can be matched with corresponding company accounts data (such as the Bureau van Dijk FAME dataset or ONS business survey data). For example, the relatively detailed explanations of the thinking behind firms' investment plans (as described in the survey) can be linked with accounting information available in company accounts. Once information is gathered on accounting data, it is possible to separate the responses in the CBI survey for firms that differ by size, region and sector. Moreover, qualitative responses in the survey on incentives and constraints on investment, and to other measures of activity such as production, sales, inventories and capacity utilisation can be compared to the quantitative information in company accounts.

This chapter contributes to existing research by creating a unique firm-level dataset consisting of data on how firms make their decisions (taken from the CBI survey data) and actual decisions made by the firm (taken from the Bureau van Dijk FAME dataset and the ABS, MBS and QCAS from the ONS). This involves using a matching key (based on firm name, address and postcode) to match to FAME (using a modified trigram matching

[2]While Lui et al. (2011a, 2011b) match the CBI dataset to the Inter-Departmental Business Register (IDBR) they focus solely on definite matches - in contrast to this chapter which develops a decision rule to allow for multiple matches and thus a larger dataset.

algorithm) and to the IDBR (based on token matching). In order to match to the IDBR researchers have to decide what to do with multiple matches. This chapter outlines a decision rule which provides a unique match among the set of multiple matches. While the creation of this decision rule was governed by a knowledge of the data and objectives of the research (namely, to link with specific ONS surveys), it provides a foundation for future researchers in matching non-ONS data to ONS data when the matching key does not always result in a set of definite matches. The matched dataset is then used in an illustrative exercise to test the directional accuracy of firm output and employment forecasts. This extends the work of Das et al. (1999) and Lui et al. (2011b) (who used the mean of the firm's subjective density forecast to define a firm-level rationality criterion) by deriving quantitative thresholds which define the range of movement for the answer bins in the CBI suite of business surveys.

The structure of this chapter is as follows: Section 2.2, Section 2.3 and Section 2.4 discuss the primary data sources of the chapter - (respectively) the CBI dataset, the Bureau van Dijk FAME dataset and various ONS business surveys (specifically the Annual Business Survey (ABS), the Monthly Business Survey (MBS) and the Quarterly acquisitions and disposals of Capital Assets Survey (QCAS)). Section 2.5 discusses how the CBI dataset is matched to the Bureau van Dijk FAME and ONS datasets. Section 2.6 tests the directional accuracy of output and employment forecasts using survey responses and company accounts data. Section 2.7 concludes.

2.2 The Confederation of British Industry (CBI) Dataset

2.2.1 Scope of the CBI Suite of Business Surveys

The CBI suite of business surveys constitutes four surveys completed by businesses operating in the UK. Participating firms provide qualitative information on a range of economic variables related to their business activity. These surveys are open to both members and non-members of the CBI. The survey suite traces its origins back to 1958 with the introduction of the Industrial Trends Survey (ITS), covering the UK manufacturing and mining industry. Since then the survey suite has expanded with the addition of the Distributive Trades Survey (DTS), Financial Services Survey (FSS) - sponsored by PWC - and the Service Sector Survey (SSS) in 1983, 1989 and 1998 (respectively), with each survey covering their eponymous industrial sectors. These augmentations to the original survey result in a continuous source of data for the UK economy (categorised by industrial sector) dating from the turn of the century. Completion of each survey is voluntary meaning firms do not have to complete consecutive surveys and in fact after completing one survey are under no obligation to participate in further survey rounds. It should be noted at this stage that analysis of this survey suite can only cover period after 2000 or period before 2000. This arises due to a change in the survey processing platform in 1999Q4 by the CBI making matching of firms before and after December 1999 impossible.

Each survey contains what the CBI label a "Basic Data Section" for the firms to compile. In this section they provide details on employees, value of direct exports (if applicable), annual turnover, geographic location, SIC code, type/nature of business (DTS and FSS only), type of organisation (SSS only - for example subsidiary or enterprise) and basic company details (such as address). While this section of the surveys provides some useful additional variables on responding firms, it's key advantage lies in providing non-anonymised company details. This allows the CBI suite of business surveys to be combined with company accounts data to provide an even greater picture of the state of business in the UK.

2.2.1.1 Distribution and Publication of the Surveys

As Table 2.1 makes clear the ITS, SSS and DTS are conducted each month while the FSS is conducted quarterly. For the ITS, SSS and DTS a basic survey - the Monthly Trend Enquiry (column 1 of Table 2.1) - is conducted each month and is supplemented each quarter by additional questions from the CBI (column 2 of Table 2.1) and the Bank of England (column 3 of Table 2.1). The CBI and Bank of England (BoE) supplementary questions are contained in the same quarterly survey for the ITS. For the SSS and DTS the Bank of England supplementary questions supplement a standard Monthly Trend Enquiry survey with the CBI supplementary questions contained in a separate quarterly survey. In addition, the Bank of England changes a number of their supplementary questions in the FSS each quarter. Collection for the survey published in month t begins around the final week of month $t-1$ with publication of results around the final week of month t. For example, the January survey round questionnaire is issued around the last week of December with the concurrent results published around the last week of January.

2.2.1.2 Core Survey Questions

Table 2.2 provides an overview of the questions contained in the Monthly Trend Enquiry for the ITS, SSS and DTS; the inclusion of questions in the survey is indicated by "Yes" or "No". Certain questions (for example on numbers employed or output) have both a prospective and retrospective nature. In other words, firms are asked to provide their

Table 2.1: Survey Timings

	Monthly Trend Enquiry	**CBI Supplementary Questions**	**BoE Supplementary Questions**
ITS	February, March, May, June, August, September, November, December	January, April, July, October	January, April, July, October
SSS	January, March, April, June, July, September, October, December	February, May, August, November	January, April, July, October
DTS	January, March, April, June, July, September, October, December	February, May, August, November	January, April, July, October
FSS		March, June, September, December	March, June, September, December

three-month ahead expectation and their past three-month backcast for these questions[3]. Note that discussion of the FSS is ignored in Table 2.2 as this survey is only run quarterly.

Output as referenced in the surveys relates to volume of production, volume of business and volume of sales for the ITS, SSS and DTS (respectively). Each question in Table 2.2 is by nature trichotomous with responding firms providing qualitative answers. As a representative example consider the question where firms are asked in each survey what their expectations are regarding demand over the next three months - firms can respond by selecting "up", "same" or "down". No quantitative style questions are contained in any of the Monthly Trend Enquiries. As Table 2.2 indicates there is a moderate degree of crossover - in particular, questions regarding the volume of output, domestic average selling prices and number of employees are present across all surveys. There are, however, a set of questions unique to the DTS. This unique set of questions asks respondents to assess the performance of a set of variables (for this month and their expectations for next month) with their past performance twelve and eleven months ago. This set of variables include volume of sales, volume of orders placed on suppliers, volume of sales, volume of stocks (in relation to expected sales), number of full-time employees, number of part-time employees, volume of internet sales and average price of goods sold over the internet (there is also an additional question asking about selling goods on the internet).

[3]The backward- and forward-looking time horizon was actually four months until July 2003.

Table 2.2: Monthly Trend Enquiry Questions

	ITS	**SSS**	**DTS**
Confidence Indicator	No	Yes	Yes
Present Order Book	Yes	No	No
Stock of Finished Goods	Yes	No	No
Output	Yes	Yes	Yes
Supply	No	No	Yes
Domestic Average Selling Price	Yes	Yes	Yes
Employees	Yes	Yes	Yes

2.2.1.3 Supplementary Survey Questions

Table 2.3 provides an overview of the supplementary questions run each quarter by the CBI. Each of the questions contained in the Monthly Trend Enquiries (i.e. Table 2.2) are also contained in the surveys with the CBI supplementary questions[4]. As is evidenced by Table 2.3 the CBI supplementary questions are more sector oriented and provide a more in-depth view of the operating environment of UK firms. Restricting attention to the Monthly Trend Enquiry alone results in the loss of this valuable information. The combined information of Table 2.2 and Table 2.3 means that the CBI suite of business surveys are a valuable resource in determining the state of business in the UK (and in particular how firms themselves view the state of business).

The Bank of England supplementary questions (run every quarter) are quantitative in nature. The questions overlap in the surveys and relate to changes (in the past twelve months, in the next twelve months and the next twenty-four months - for general selling price) in the general level of selling prices in the UK markets in which the firm operates, the firm's own average selling price and the average cost per employee. In addition, the SSS contains a question regarding the ability of a firm to increase its volume of activity given its current resources (in particular if it can and, if it can, then by how much).

2.2.2 Sample Frame

This section demonstrates clearly the impressive panel structure of the CBI suite of business surveys, in particular the extensive coverage and continuity of firms (which allows for the tracking of individual firms across time) across four sectors. What follows refers to the supplementary quarterly surveys.

[4]In addition to the questions listed in Table 2.3, the FSS also contain a set of additional questions which change each quarter (as these questions change on a regular basis they are not considered in this study).

Table 2.3: CBI Supplementary Questions

	ITS	SSS	DTS	FSS
Optimism	Yes	Yes	No	Yes
Investment	Yes	Yes	Yes	Yes
Capacity	Yes	No	No	No
Employees	Yes	Yes	Yes	Yes
Total New Orders	Yes	No	No	No
Deliveries	Yes	No	No	No
Stock	Yes	No	Yes	No
Average Cost per Output	Yes	No	No	No
Average Selling Price	Yes	Yes	Yes	No
Present Order Book	Yes	No	No	No
Factors Limiting Output	Yes	Yes	No	Yes
Factors Limiting Export Orders	Yes	No	No	No
Competitiveness	Yes	Yes	No	No
Present Fixed Capacity	Yes	No	No	No
Investment Influences	Yes	Yes	No	Yes
Present Level of Business	No	Yes	No	Yes
Value of Business	No	Yes	No	Yes
Average Commission	No	Yes	No	Yes
Total Costs per Employee	No	Yes	No	No
Profitability	No	Yes	No	Yes
Expansion Intentions	No	Yes	No	No
Supply from Imports	No	No	Yes	No
Overall Business Situation	No	No	Yes	No
Marketing Expenditure	No	No	No	Yes
Staff Turnover	No	No	No	Yes
Staff Costs	No	No	No	Yes
Value of Insurance Claims	No	No	No	Yes
Value of Fee	No	No	No	Yes
Value of Net Interest	No	No	No	Yes
Value of New Business	No	No	No	Yes
Average Spreads	No	No	No	Yes
Total Operating Costs	No	No	No	Yes
Average Operating Costs	No	No	No	Yes
Value of Non-Performing Loans	No	No	No	Yes
Value of Insurance Contracts	No	No	No	Yes

2.2.2.1 Minor Cleaning of the Sample

Before examining the CBI dataset proper, some cleaning and matching techniques are employed. First, firms without a unique identification number are dropped from the sample. For reasons of anonymity, each firm that participates in at least one survey is provided with a unique identification number by the CBI so their responses can be tracked through subsequent survey waves. However, within the dataset a number of survey responses are not paired with a unique identification number. While it could be the case that these survey responses are all generated by one firm there is no guarantee this is true. Therefore, in order to ensure the highest level of accuracy possible all survey responses without a corresponding unique identification number are dropped[5].

Second, firm responses recorded as N/A are designated as missing responses. For each trichotomous style question firms have a "fourth" option: N/A. For example, in the ITS when asked for their expectation for volume of demand firms can reply up, same, down or N/A. Recording these N/A answers as missing ensures calculating the percentages of firm responses to the survey questions are more accurate.

2.2.2.2 Timespan of the Survey Suite

Table 2.4 indicates the timespan available for each survey in the CBI dataset. Evidently both the ITS and DTS have the largest span - with 82 and 81 consecutive quarters of survey responses (respectively). However, the same is not true of the FSS - data is missing for 2015Q4, 2016Q1, 2016Q2, 2016Q4, 2019Q3 and 2019Q4. In the case of the SSS, survey responses prior to 2005Q4 are available but not the questions that were in the survey for these dates. Finally, it is worth highlighting that just because a survey runs for x number of consecutive quarters does not mean there are x observations for each survey question. For example, while there are 81 quarters of data for the DTS, questions regarding the quarterly expectation and realisation of volume of sales only began in 2003Q4.

Table 2.4: Span of the CBI Suite of Business Surveys

	First Period	**Final Period**
ITS	2000Q1	2020Q2
SSS	2005Q4	2020Q1
DTS	2000Q1	2020Q1
FSS	2000Q4	2020Q1

2.2.2.3 Number of Firm Participants

The coverage of the survey (in terms of the number of participating firms and the number of survey responses) is presented in Table 2.5. The number of participating firms are the number of distinct firms partaking in each survey round while total survey responses

[5]Overall, this has a minimal effect on the dataset. The ITS lost 22 observations, the SSS 12 observations, the DTS 20 observations and the FSS 0 observations.

detail the number of responses generated by these distinct participants. For example, if Firm A participates in the ITS by completing eight surveys from 2000Q1 to 2020Q2 then this is recorded as one observation in the "Number of Firms" column and eight observations in the "Number of Responses" column in Table 2.5. Furthermore, Firm A does not necessarily have to complete all eight surveys consecutively to be recorded in Table 2.5. For example, Firm A can complete three consecutive surveys, drop out for a number of quarters and later complete five consecutive surveys.

Table 2.5 shows the CBI dataset predominantly consists of manufacturing and mining firms (i.e. respondents to the ITS). In fact, there are nearly three times the number of firms in the ITS than in the survey with the next highest number of participants (i.e. the SSS). Over the course of the sample the average firm in the ITS completed around ten surveys; in the SSS firms completed around six surveys; in the DTS firms completed nine surveys and in the FSS firms completed around six to seven surveys. The ability to track individual firm responses throughout the sample period is an undoubted strength of this suite of business surveys.

Table 2.5: Sample Size of CBI Dataset

	Number of Firms	**Number of Responses**
ITS	4,718	46,996
SSS	1,585	9,900
DTS	1,493	13,680
FSS	1,112	7,252

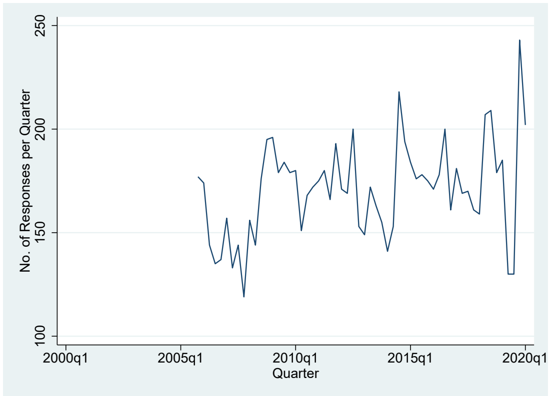
Source: The Confederation of British Industry (CBI) suite of business surveys. The Industrial Trends Survey (ITS) covers the manufacturing and mining sector. The Service Sector Survey (SSS) covers the service sector. The Distributive Trades Survey (DTS) covers the distributive trades sector. The Financial Services Survey covers the financial services sector.

2.2.2.4 Continuity of Observations in the Survey

Voluntary participation in the CBI suite of business surveys means that firms are under no obligation to complete surveys subsequent to their first. As a result, the number of participating firms and the continuity of observations from participating firms varies over the course of the sample. Figure 2.1a to Figure 2.1d plot the number of participating firms in each survey over time. The ITS and DTS (Figure 2.1a and Figure 2.1c, respectively) have both witnessed a downward trend over the course of the sample (with any increase in responses proving only temporary) while the SSS (Figure 2.1b) has witnessed a somewhat sustained and moderate increase. The FSS (Figure 2.1d) initially witnessed a steady decline in responses but this has partially been reversed since 2007. Despite its continual downward trend in survey responses the ITS consistently remains the largest of the four surveys in terms of participating firms. These conclusions are further reinforced by Table 2.6 - which shows how the number of firm participants has changed between 2000-2006, 2007-2012 and 2013 to the end of the sample. The number of participating firms has declined across each time period in each survey - except for the SSS.

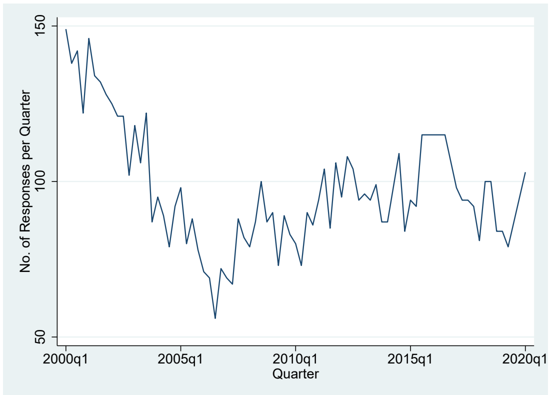
Figure 2.1: Responses per Quarter

(a) Manufacturing and Mining Firms



(b) Service Firms

(c) Distributive Trades Firms



(d) Financial Services Firms

Further information on participating firms is provided by Figure 2.2a to Figure 2.2d which graph the number of firm entries and exits for each of the surveys over time. A firm entrant is a firm which did not complete the survey in $t-1$ but completes the survey in t, while an exiting firm completed the survey in $t-1$ but does not in t. Figure 2.2a to Figure 2.2d highlight that the number of firms entering per quarter does not compensate for the number of firms leaving per quarter. Nevertheless, the CBI dataset does demonstrate a degree of continuity among participating firms with 79.82%, 74.42%, 81.18% and 70.49% of firms in the ITS, SSS, DTS and FSS completing two or more consecutive surveys (respectively). However, the trend for each survey of the survey suite is clear: there

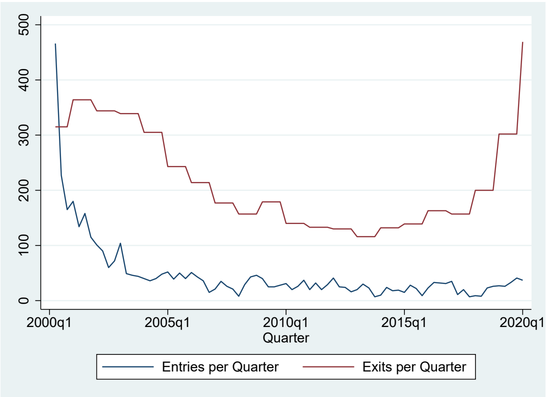
Table 2.6: How the Number of Firm Participants has Changed over time?

	ITS	SSS	DTS	FSS
2000-2006	3,345 (23,668)	329 (767)	877 (6,664)	563 (2,960)
2007-2012	1,818 (11,352)	750 (4,040)	604 (3,548)	445 (2,113)
2013-2020	1,678 (11,976)	1,077 (5,093)	599 (3,468)	466 (2,179)

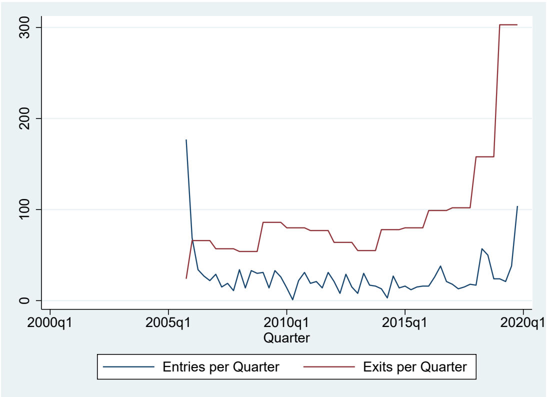
Note: Parenthesised figures refer to the number of survey responses.

is a declining number of firms consecutively completing a large number of surveys. In addition, the largest percentage of firms only complete one survey (20.18% for the ITS, 25.58% for the SSS, 18.82% for the DTS and 29.51% for the FSS).

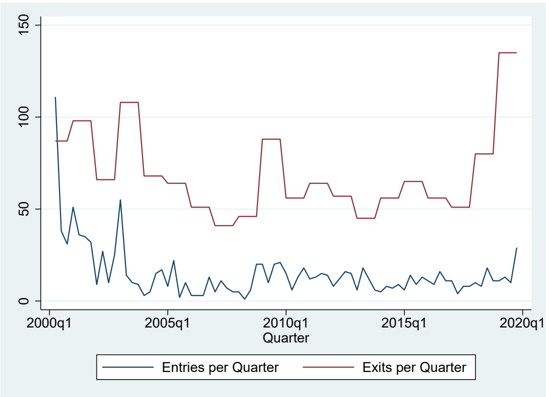
Figure 2.2: Entry and Exit of Firms



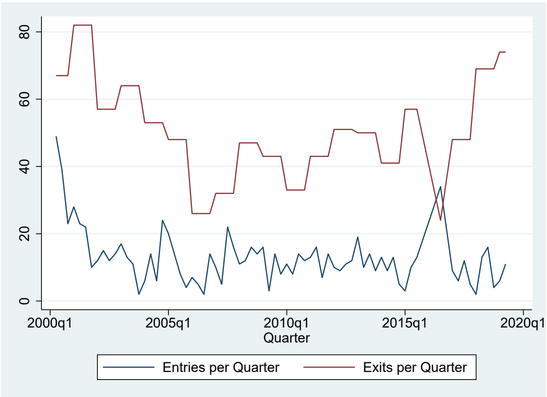
(a) Manufacturing and Mining Firms



(b) Service Firms



(c) Distributive Trades Firms



(d) Financial Services Firms

2.2.3 Characteristics of Firm Participants

Table 2.7 provides an overview of the characteristics of firm participants - namely their size, industrial classification and geographic location. Using the usual classification scheme, firm size is defined by numbers employed: micro (0 - 9 employees), small (10 - 49 employees), medium (50 - 249 employees) and large (250+ employees). The CBI does not ask firms to provide an exact employee number but rather to select an appropriate bin size in the survey - and employee numbers are then recorded as the upper limit of each bin. This collection methodology is subject to two limitations. First, the bin sizes have changed over the course of the sample. Second, the bin sizes do not reflect the standard firm size classification. To best capture firm size micro, small and medium has been aggregated into one classification in Table 2.7.

Table 2.7 aggregates industrial classifications for the ITS into primary and secondary designations - as individual survey waves in the survey suite use different SIC codes[6]. Primary manufacturing is defined as mining and the wood, coke, rubber, base metals, machinery and other manufacturing subsectors with secondary manufacturing being defined as the remaining manufacturing subsectors. For example, there are 1,623 primary manufacturing firms in the ITS generating 16,793 survey responses in Table 2.7. The remaining surveys in the survey suite are not aggregated into primary or secondary designations and instead are classified based on the survey they have opted into (see Table 2.5).

Location is defined according to Nomenclature of Territorial Units for Statistics (NUTS) level one. In Table 2.7 "South-East" and "London" are aggregated into one classification. The second classification consists of all remaining NUTS level classifications[7]. However, geographical location data is missing for 84.42% and 84.6% of survey responses in the DTS and FSS (respectively). This potentially reflects the nature of these industries with firms either being in multiple locations or operating on a scale larger than one geographical location.

2.2.4 The Benefits of Utilising Firm-Level Survey Data

What are the benefits of utilising firm-level survey data? This can be answered by discussing the specific strengths of the CBI suite of business surveys and explicitly refuting perceived weaknesses.

[6] The ITS primarily uses SIC80, the SSS primarily the SIC92 and the DTS and FSS both use SIC07 in their industrial classification.

[7] These are Wales, Scotland, Northern Ireland, North-East, North-West, Merseyside, Yorkshire and the Humber, East Midlands, West Midlands, South West and East of England.

Table 2.7: Characteristics of Firm Participants

	ITS	**SSS**	**DTS**	**FSS**
Micro, Small and Medium Firms	3,812 (37,621)	1,102 (6,396)	920 (7,121)	780 (4,750)
Large Firms	1,327 (9,375)	557 (3,504)	654 (6,559)	410 (2,502)
Primary Manufacturing	1,623 (16,793)			
Secondary Manufacturing	3,148 (30,200)			
Firms in South-East and London	996 (9,589)	469 (2,251)	77 (328)	141 (538)
Other Geographic Areas	3,791 (37,407)	1,152 (7,649)	1,452 (13,352)	1,055 (6,714)

Source: Basic Data Section of the ITS, SSS, DTS and FSS. Parenthesised figures refer to the number of survey responses. Firm size is defined by numbers employed: micro (0 - 9 employees), small (10 - 49 employees), medium (50 - 249 employees) and large (250+ employees). Primary manufacturing is defined as mining and the wood, coke, rubber, base metals, machinery and other manufacturing subsectors with secondary manufacturing being defined as the remaining manufacturing subsectors. Location is defined according to Nomenclature of Territorial Units for Statistics (NUTS) level one. Other geographic areas refer to Wales, Scotland, Northern Ireland, North-East, North-West, Merseyside, Yorkshire and the Humber, East Midlands, West Midlands, South West and East of England.

2.2.4.1 Strengths of the CBI Suite of Business Surveys

The CBI suite of business surveys possesses a number of strengths which make it an excellent data source. First, in contrast to official statistics it provides a timely release of data. Official statistics are published with a lag and then are often subject to revision. However, as established from Table 2.1 data from the CBI is quickly available for inspection and analysis. In particular, firm-level forecasts (i.e. expectations) for each quarter are made available at the end of the first month of said quarter. Similarly, firm-level backcasts for the previous quarter are available at the end of the first month of the succeeding quarter. Thus, policymakers are quickly able to understand the state of the economy and react accordingly. For example, the CBI dataset is capable of providing reliable, real-time economic data to policymakers (and researchers) during the COVID-19 pandemic.

Second, the CBI dataset is a substantial one - covering a large number of firms over a significant time period. Focusing on the time-series aspect of the dataset, manufacturing and mining firms are surveyed by the CBI for over sixty years, while those with the shortest period of coverage (service firms) are surveyed for over twenty years. This time frame covers a number of business cycles and economic events. For example, restricting attention to post-2000 ensures events such as the dot-com bubble, financial crisis, great recession, subsequent recovery and period around Brexit referendum are covered. Furthermore, the cross-section element of this dataset is equally substantial with a large number of firm participants each survey round. Moreover, with the inclusion of the basic data section in each survey round this cross-section can be further analysed. Specifically, firms can be classified based on their location in the UK, their industry activity (using their SIC code), their firm size (based on employee numbers) and whether they are exporters. Thus, the CBI dataset contains information not only on the number of participants but also details on these participants. Furthermore, due to the nature of the survey suite individual firms can be tracked across time allowing for changes in firm responses to be examined as well as more in-depth analysis.

Third, as demonstrated by Table 2.2 and Table 2.3 the CBI dataset contains information covering a wide range of economic variables. In fact, the greater the scope of variables covered by the CBI suite of business surveys the greater the ability to gain an insight into the thinking of economic agents operating in the UK. Crucially, the CBI suite of business surveys encapsulates the viewpoint of market participants conveying the “frame of mind of economic agents” as opposed to the views of non-market participants (Kabundi, 2004, p.6).

2.2.4.2 Discussion of the Qualitative Nature of the CBI Suite of Business Surveys

The CBI suite of business surveys predominately rely on questions with qualitative answers - i.e. trichotomous style questions with “up/same/down” (or equivalent) answer bins. Rather than firms selecting from one of three answer bins would it not be better if they provided a point estimate for the variable in question with a corresponding probability distribution? This solves resorting to quantification techniques and provides a ready expectation or uncertainty series. Indeed both Pesaran (1987) and Lui et al. (2011b) espouse augmenting existing qualitative surveys with explicit quantitative questions. Yet both Pesaran (1987) and Pesaran and Weale (2006) argue that qualitative tendency surveys are less likely suffer from measurement (and sampling) errors. Indeed, it seems reasonable to argue that it is easier for a firm to report they expect output to go “up” in the next three months than it is to provide a point estimate. Moreover, there are perfectly reasonable and justifiable quantification techniques. On this basis, reliance on qualitative data is not an issue. Furthermore, through reference to the CBI Answering Practices Survey (APS)[8] other perceived issues regarding the use of qualitative data can be refuted. For example, the APS shows there is no confusion regarding what firms mean

[8]See Appendix B for details.

by "up/down" or indeed the magnitude of change in a variable required for a firm to select "up/down".

2.3 The Bureau van Dijk FAME Dataset

The Bureau van Dijk FAME dataset is an annual dataset of company accounts data from firms registered with Companies House. This data is available from 2000 to 2018. There are around 12.6 million firms in the FAME dataset, of which 5.6 million are active and 7 million are inactive. Of the 5.6 million active firms, 3 million have a detailed financial format, 300,000 have a summary financial format and around 2.3 million do not have filed accounts (either they are not required or have not yet filed their first accounts).

For each firm the FAME dataset records basic firm details, including (among other things) firm name (including previous firm names), Companies House registration number (CRN), registered office address, SIC 2007 code, audit details, number of employees, company type, company status and details on directors (current and past). In addition, the FAME dataset includes 63 profit and loss items, 75 balance sheet items, 10 cash-flow items and 29 financial and profitability ratios. It also includes data on credit scores and limits, Gazette data[9] and six years of County Court Judgement history and mortgage data. For quoted firms the FAME dataset includes main exchange and ticker symbol, security and price information, London Stock Exchange indices, current and annual stock data and valuations, daily, weekly and monthly pricing series and market capitalisation figures and advisors.

2.4 The Office of National Statistics (ONS) Dataset

2.4.1 The Inter-Departmental Business Register (IDBR)

Office of National Statistics (ONS) business surveys are mostly run using data from the Inter-Departmental Business Register (IDBR). The IDBR is a register of all businesses in the UK which employ at least one person through a Pay-As-You-Earn (PAYE) tax scheme and/or earn above the VAT threshold in turnover in a year[10]. Businesses on the IDBR are structured to combine data relating to different parts (or levels) of the business. For example, tax data may relate to a slightly different business entity than

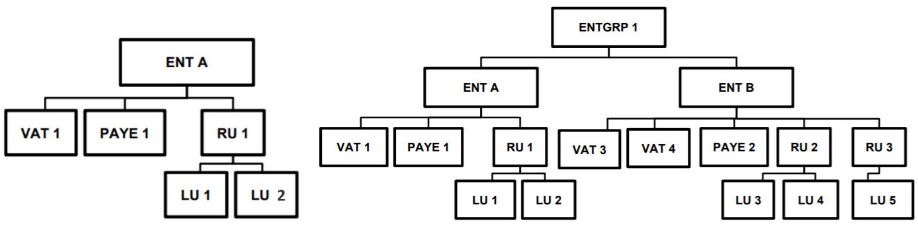
[9] Official data related to company insolvency and deceased estates data.

[10] The IDBR also contains organisations that are not "businesses" assuming they meet one of the rules for inclusion (usually the PAYE rule). Examples of this include (but are not limited to) government departments, schools and charities.

what is commonly understood to be the "business", which might in turn be different from the statistical unit. These levels of the business structure on the IDBR (in broadly descending levels of hierarchy) are the Enterprise Group (EG)[11], the Enterprise (ENT)[12], VAT reference (VATref)[13], PAYE reference (PAYEref)[14], Reporting Unit (RUref)[15] and Local Unit (LUref)[16].

Figure 2.3a and Figure 2.3b depict two stylised examples of business structure on the IDBR. Figure 2.3a shows a simple business where the tax units, enterprise unit and statistical units are all the same. This is typical for a large number of small businesses on the IDBR (which are the majority by number but comprise a minority of employment and turnover). Figure 2.3b is a more typical (hypothesised) structure for a medium-to-large business on the IDBR. In this there are many-to-one relationships between most levels of the structure.

Figure 2.3: Example Business Structures on the IDBR



(a) Simple Business Structure

(b) Complex Business Structure

Note: These are both stylised depictions and are hypothetical and not exhaustive.

2.4.2 Various ONS Business Surveys of Interest

ONS business surveys of interest which can be matched to the CBI dataset include the Annual Business Survey (ABS)[17], the Monthly Business Survey (MBS)[18], the Quarterly acquisitions and disposals of Capital Assets Survey (QCAS)[19]. For each of these surveys

[11]The parent company (or similar).

[12]Usually the legal entity and what is commonly understood to be the "business".

[13]The Value Added Tax (VAT) reference associated with part of the business. There can be multiple for each ENT - especially for complex businesses.

[14]The Pay As You Earn (PAYE) income tax reference associated with part of the business. There can be multiple for each ENT - especially for complex businesses.

[15]A statistical unit (agreed between the ONS and the business as the appropriate level for survey responses).

[16]A physical location (for example a shop, office or factory). For large businesses there can be many associated with each RUref.

[17]The ABS replaced the Annual Business Inquiry - part 2 in 2009

[18]The MBS was an amalgamation of the Monthly Production Inquiry (MPI) and the Monthly Inquiry into the Distribution and Services Sector (MIDSS) in 2010M1

[19]The QCAS was an update of the Quarterly Capital Expenditure Survey (QCES) in 2015Q1

the sample frame is the IDBR and stratified random sampling is used (with large firms always included for the ABS and MBS). Data for the ABS, MBS and QCAS is available from 2000-2018, 2000M01-2018M09 and 2000Q1-2016Q1 (respectively). The sample size for the ABS, MBS and QCAS is 73,000 (63,000 in Britain and 11,000 in Northern Ireland), 32,000 and 27,000 (respectively). The ABS provides quantitative measures of total turnover; approximate gross value added at basic prices; total purchases of goods, materials and services; total employment; total average employment; total employment costs; total net capital expenditure and total stocks and work in progress. The MBS measures total turnover; export turnover; total new orders; export new orders and employment. The QCAS measures major improvements and construction work; machinery and equipment; intellectual property assets and total value of acquisitions and proceeds from disposal of assets.

2.5 Matching the Datasets

The primary reason for matching the CBI dataset to other microdata sources (such as the Bureau van Dijk FAME dataset or the various ONS business surveys) is due to the unique economic data it contains. For example, the CBI dataset provides a direct measure of expectations (regarding a range of variables), investment constraints and capacity - variables not readily available in other sources. Most business surveys, including most of those conducted by the ONS, collect only quantitative data, and then usually only that required for official statistics and National Accounting. Non-official business surveys, such as the CBI surveys, offer a different perspective on the business economy by collecting qualitative data and less common variables. Combining quantitative with qualitative data can unlock new possibilities for analysis, and therefore, matching the CBI data with other microdata sources opens new avenues of research and enhances existing ones.

Matching data requires a matching key that allows records from one dataset to be identified in a second dataset and then linked. The quality of the matches depends on the uniqueness (and existence) of the key. Detailed analysis (including comparisons) of text matching algorithms are found in (but not limited to) Zobel and Dart (1995), Pfeifer et al. (1996), Christen (2006), Rafflo and Lhuillery (2009), Mohd et al. (2014), Schoen et al. (2014), Medhat et al. (2015), Gali et al. (2016) and Al-Hagree et al. (2019). While such detail is beyond the scope of this chapter, a brief overview of these techniques (including worked examples) is informative - both in terms of discussing how the CBI dataset, Bureau van Dijk FAME dataset and various ONS business surveys are matched and how this matching compares with other potential techniques.

Vectorial decomposition matching algorithms compare the characters of words or phrases (such as a business name) for similarity. For example, a general N-gram decomposition (for N of any size) splits a word or phrase into moving "grams" (or set of characters - including blank spaces) of size N. The matching algorithm of Bureau van Dijk (used to match the CBI and FAME datasets using firm names as unique identifiers)[20] is based on a general (but modified) N-gram decomposition. Before matching, Bureau van Dijk applies normalisation rules to firm names (for example, removing company suffixes such as "Ltd" and "PLC" and blank spaces in firm names). The aim of this parsing is to reduce noise in firm names in order to improve the set of potential matches. Matching is then implemented using a trigram algorithm (i.e. an N-gram algorithm with N=3), where firm names are split into moving "grams" of three based on individual words within the firm name. For example, "Bureau van Dijk Ltd" becomes "BUREAU", "VAN" and "DIJK" with the following trigram decompositions: "BUR", "URE", "REA", "EAU", "VAN", "DIJ" and "IJK". This process yields a set of potential match candidates for each firm in the data being matched, where candidates in the FAME data are selected and ranked on the degree of congruence between their trigram decomposition and the firm name decomposition in the data being matched.

The advantage of this Bureau van Dijk matching process is its ability to overcome issues related to spelling mistakes, typing errors, word order and special characters. For example, suppose "Bureau van Dijk Ltd" is misspelled as "Buro van Dijk". The misspelled firm name is transformed to "BURO", "VAN" and "DIJK" with the following trigram decomposition "BUR", "URO", "VAN", "DIJ" and "IJK". Then "BUR", "VAN", "DIJ" and "IJK" are common decompositions between the correct and incorrect firm name spelling, resulting in "Bureau van Dijk Ltd" as a potential match candidate for "Buro van Dijk". As this example demonstrates, the Bureau van Dijk matching algorithm minimises the risk of errors arising from discrepancies in firm name storage (for example related to company suffixes) and "fat-finger errors" (such as spelling mistakes) - thus increasing confidence in the accuracy of the matching process.

Another example of vectorial decomposition is token matching which splits firm names into blocks, called tokens, according to blank spaces. This approach is used by the IDBR support team at ONS by tokenising the name, address and postcode of firms[21]. For example, "Bureau van Dijk Ltd" has the following decomposition: "Bureau", "van", "Dijk" and "Ltd". Any random combination of these decomposed blocks is matched to "Bureau van Dijk Ltd". In contrast to the trigram decomposition matching process described above, token matching is unable to handle spelling mistakes or grammar.

Other matching processes include phonetic matching and edit-distance matching[22]. Pho-

[20]Firm names (and a matching key to firm-level survey responses) were provided by the CBI.

[21]See Section 2.5.1 for further details.

[22]Neither of these algorithms have been applied in this work - they are included for completeness to

netic matching algorithms compare firm names using distinguishing units of sound. Three common examples of phonetic matching are Soundex, Phonex and Phonix. Soundex is implemented as follows: keep the first letter of the word and replace all remaining letters with the Soundex phonetic codes[23], then remove consecutive duplicates of the Soundex phonetic codes, then remove all 0's and keep the first four characters of the resulting code. For example, "BUREAUVANDIJK" becomes "b615". Similarly, both "BUROVANDIJK" and "BUROVANDYKE" become "b615". This example shows how phonetic matching algorithms are beneficial for treating pronunciation similarity in firm names (especially, if the firm names are initially supplied verbally). For example, telling a researcher to match "Bureau van Dijk Ltd" (and providing no written form of the firm name) could result in the researcher searching for "Buro van Dyke Ltd". The Soundex algorithm ensures "Bureau van Dijk Ltd" is a match candidate for "Buro van Dyke Ltd". Both the Phonex and Phonix matching algorithms follow a similar structure to Soundex but also involve letter-group transformations. Phonetic matching algorithms are language dependent and in the case of Soundex, Phonex and Phonix are developed for the English language (and thus require modification to be applied to other languages - but this is not true for all phonetic matching algorithms, such as the Double Metaphone algorithm).

Edit-distance matching algorithms compare words or phrases using the number of operations needed to gain similarity between strings. An example is the Damerau-Levenstein matching algorithm which compares firm names for additional letters, missing letters and substituted letters. Each of the operations required to achieve similarity incurs a penalty of one. Positive matches are then those with the lowest number of operations (or penalties) required to achieve similarity. This matching algorithm can be enhanced by altering the penalty for various operations required to achieve similarity.

2.5.1 Matching to the IDBR

Matching non-ONS business data to ONS business data can be challenging as non-ONS data rarely has the RUref (or any other reference number compatible with the IDBR). The matching key for matching the CBI dataset to ONS data consisted of firm-name, firm address and postcode. This matching key first requires matching the CBI dataset to the IDBR (which contains the names and addresses of all parts of the business structure). The IDBR support team at ONS implement matching using a matching software called IIR[24] which tokenises the firm name, firm address and postcode. It then calculates a propensity match score against each record on the IDBR[25]. The record on the IDBR that

give the reader a brief overview of potential matching techniques.

[23]The Soundex code is 0: a e h i o u w y; 1: b f p v; 2: c g j k q s x z; 3: d, t; 4: l; 5: m, n; 6: r.

[24]Provided by "Informatica".

[25]Scores are produced for name, address and postcode.

has the closest match (i.e. highest propensity match score) is returned. The CBI dataset was matched against all units on the IDBR (i.e. RUref, ENT, PAYEref, VATref and LUref) since the unit of observation in the CBI data was unclear. This matching process results in definite, multiple and no matches. Definite matches are when only one record has a propensity match score above 84[26]. Multiple matches occur when there are multiple records with a propensity score match above 84. If no record scores above 84, then no match is returned.

In the case of multiple matches, a choice needs to be made regarding which record to use. The primary purpose of matching the CBI dataset to the IDBR is to ultimately match the CBI data to the ABS, MBS and QCAS. Thus matches are only useful when featured in one or more of these surveys. Using microdata available inside ONS from several years of each survey, survey scores (indicating the presence in the survey data of each RUref) in each period are constructed. Each RUref received a survey score equal to the fraction of surveys it had appeared in over a considerable period of time. A survey score of one means presence in all surveys in the period used, while a survey score of zero means it never appeared. The survey scores were then averaged across the three surveys (since all were equally important to the analysis). The survey scores and data on employment size (from the 2019Q4 snapshot of the IDBR) are matched onto each multiple match RUref. Selection of a unique match among the set of multiple matches is based on the following allocation rules. First, as the same RUref can appear in the multiples matches multiple times for the same company[27] de-duplicate the list and if only one RUref is left use that one. Second, if more than one option match to the survey scores then select the one with the highest survey score - assuming no other option is within 5%. For those that are within 5%, if only one of them appears at least once in all the surveys (ABS, MBS and QCAS) - select it. For those that are within 5%, and none are in all the surveys (ABS, MBS and QCAS), select the one with largest employment[28]. Third, if they haven't appeared in any of the three surveys (i.e. the survey score is zero) then chose the one with largest employment. Rules two and three generate the most matches.

[26]This is an arbitrary threshold chosen by the IDBR support team at ONS.

[27]Since it matches to different parts of the same entity on the IDBR. For example LUref, RUref and VATref are all part of the same business structure and all corresponding to the same RUref.

[28]Choosing a larger business unit (RUref) from the same business entity is preferable, since it likely better corresponds to the CBI survey concept of a business.

2.5.2 Match Rates between the CBI and FAME Datasets

Table 2.8 provides the match rates between the CBI and FAME datasets[29], showing an overall match rate of about 50% between the two data sources. The match rate across industrial sectors (i.e. across the four CBI surveys) is approximately consistent with the overall match rate - with firms in the ITS being most likely to be matched.

Based on data collected by the CBI in the "Basic Data Section" of each survey, match rates based on firm size and geographic location can be examined. For example, the match rate among large firms in the CBI dataset is quite successful at 72.3%[30]. In fact, only the FSS has a large firm match rate below 70%. However, this successful match rate is not replicated for micro, small and medium firms - only 41.7% are matched with FAME. This is also reflected across individual surveys with only micro, small and medium firms in the ITS having a match rate exceeding 45%. In fact, not even a third of such firms in the DTS are matched. Thus, large firms in the CBI dataset are far more likely to be matched to the FAME dataset (both overall and in individual surveys) compared to micro, small and medium firms. In fact, in the latter case it is more likely that they will not be matched to the FAME dataset than matched. This makes sense as FAME is more likely to hold data for larger businesses as they are more likely to be required to file financial accounts than smaller businesses (and those accounts are less likely to have errors due to higher levels of audit and scrutiny).

Such disparity in match rates does not occur across different geographies. In fact, the match rates across geographical location broadly reflect the overall match rate. For example, the match-rate of firms located in London or the South East is 48.2% while the match rate of firms in other geographic locations is 50.2%[31] - both broadly consistent with the overall match rate of 49.8%. These match rates are broadly reflected across the individual surveys - except for the DTS which only has a match rate of 37.9% of firms located in London or the South East. Finally, the match rate between the CBI and FAME datasets has changed over time - exhibiting a hump-shaped response. Overall the match rate at the end of the sample is greater than the match rate at the beginning. However, the greatest match rate occurs in the middle of the sample - corresponding to the time around the Great Financial Crisis and its aftermath. This pattern is reflected across each of the individual surveys - except for the ITS, which effectively manages to sustain its improvement in match rates.

[29]This section discusses the match rate between the FAME dataset and the quarterly CBI survey returns - as these are the surveys which contain the most detailed (and thus most beneficial) information. This dataset consists of firm responses and company accounts data from 2000 to 2018.

[30]Large firms are defined as having 250 or more employees while micro, small and medium firms have fewer than 250 employees. Due to how the CBI records employee numbers in the survey a more detailed breakdown of micro, small or medium firms is not accurately available.

[31]Location is defined according to Nomenclature of Territorial Units for Statistics (NUTS) level one.

Table 2.8: Match Rates between the CBI and FAME Datasets

		Full CBI	**ITS**	**SSS**	**DTS**	**FSS**
Full CBI		49.8	50.7	50.2	47.7	48
For:						
	Micro, Small and Medium Firms	41.7	45.7	35.8	31	41.9
	Large Firms	72.3	73	77.2	71.9	63.5
	Firms in South-East and London	48.2	48.9	46.2	37.9	53.9
	Other Geographic Areas	50.2	51.1	51.6	48.4	48.1
	2000-2006	45.4	46.9	44.6	40.7	43.6
	2007-2012	58.1	60.1	53.3	60.1	55.3
	2013-2018	54.8	59.5	49.7	54.7	49

Note: Match rates are percentages to one decimal place. Column 1 (Full CBI) consists of all firms in the CBI dataset (i.e. the sum of all firms which have completed the individual CBI surveys). Columns 2-5 provide a breakdown of match rates by survey. Column 2 (ITS) are the match rates for firms which have completed the Industrial Trends Survey only. Column 3 (SSS) are the match rates for firms which have completed the Service Sector Survey only. Column 4 (DTS) are the match rates for firms which have completed the Distributive Trades Survey only. Column 5 (FSS) are the match rates for firms which have completed the Financial Services Survey only. Each row describes how the sample of firms in the CBI dataset can be split for the purposes of matching to the FAME dataset. Row 1 is the full sample of survey firms while Row 2-8 splits the survey sample by firm size (Row 2 and Row 3), by geographic location (Row 4 and Row 5) and over time (Rows 6 to 8).

2.5.3 Match Rates between the CBI dataset and the IDBR

Table 2.9 provides the match rates between the CBI and FAME datasets and the IDBR[32]. While all businesses responding to the CBI survey should be on the IDBR (given the nature of the IDBR as a complete register of UK businesses), not all will be found for various reasons. These will include errors (including spelling errors) in either dataset, non-contemporaneous data or limitations of the matching algorithm. In practice a match rate of 89.5% between the full CBI dataset and the IDBR is achieved. Each individual survey in the CBI dataset has a match rate exceeding 80% with the IDBR. The match rates between the CBI dataset and the IDBR are far greater than the corresponding match rates with the FAME dataset in Table 2.8. Of the total number of matches, around a quarter to a third are due to multiple matches. Excluding these would give a lower match rate yielding a smaller dataset - thus, potentially losing good matches and reliable data.

The high match rates between the CBI surveys and the IDBR continues if the sample is split by firm-size, geographic location and over time. This is in sharp contrast to the corresponding match rates presented in Table 2.8, when matching to the FAME dataset.

[32]To maintain consistency with the Bureau van Dijk FAME matching exercise only CBI data from up until 2018Q4 is used for matching to the IDBR.

For example, the great disparity in match rates based on firm size present when matching to the FAME dataset is absent in Table 2.9. In addition, the hump-shaped match-rate between the CBI and FAME over time is now replaced with a more consistent (and higher) match rate. Specifically, across each of these classifications the match rates between the ITS, SSS, DTS and FSS and the IDBR exceed 80%. Finally, concentrating only on CBI records matched to FAME, the match rate with the IDBR still exceeds 90% for the ITS, SSS and FSS with a match rate of 87.4% for the DTS.

Overall the match rate between the CBI dataset and the IDBR is better than the FAME match rates. Only for the subsample of large firms do FAME match rates consistently exceed 50%. However, even this high match rate is outperformed by the corresponding IDBR match rates.

Table 2.9: Match Rates between the CBI and FAME datasets and the IDBR

		Full CBI	**ITS**	**SSS**	**DTS**	**FSS**
Full CBI		89.5	87.9	88.5	82.6	88.2
Of which:						
	Definite IDBR Matches	64.6	57.5	65.8	50.9	61.9
	Multiple IDBR Matches	24.9	30.4	22.7	31.6	26.3
For:						
	Micro, Small and Medium Firms	89.6	86.4	86.7	79.9	87.6
	Large Firms	88.9	90.5	91.6	87.6	89.6
	Firms in South-East and London	87.8	86.6	93.1	88.0	87.7
	Other Geographic Areas	89.8	88.5	88.4	82.2	88.3
	2000-2006	88.4	88.6	87.5	80.4	87.4
	2007-2012	91.7	88.6	91.2	85.3	90.2
	2013-2018	92.7	89.3	92.2	87.9	91.1
CBI & FAME		92.2	91.9	93.5	87.4	91.8

Note: Match rates are percentages to one decimal place. Column 1 (Full CBI) consists of all firms in the CBI dataset (i.e. the sum of all firms which have completed the individual CBI surveys). Columns 2-5 provide a breakdown of match rates by survey. Column 2 (ITS) are the match rates for firms which have completed the Industrial Trends Survey only. Column 3 (SSS) are the match rates for firms which have completed the Service Sector Survey only. Column 4 (DTS) are the match rates for firms which have completed the Distributive Trades Survey only. Column 5 (FSS) are the match rates for firms which have completed the Financial Services Survey only. Each row describes how the sample of firms in the CBI dataset can be split for the purposes of matching to the IDBR. Row 1 is the full sample of survey firms, and rows 2 to 3 shows the contribution from Definite matches and Multiple matches. Rows 4-10 split the survey sample by firm size (Row 4 and Row 5), by geographic location (Row 6 and Row 7) and over time (Rows 8 to 10). Row 11 is the sample of the matched CBI and FAME dataset.

2.5.4 Match Rates between the CBI Dataset and ONS Business Surveys

Table 2.10 provides the match rates between the CBI dataset and the ABS, MBS and QCAS. For example, there is a match rate of 50.4% between the ITS and the ABS[33]. The match rates between the FSS and the ONS business surveys are substantially poorer than the corresponding match rates for the remaining CBI surveys - reflecting the nature of firms participating in the FSS. Specifically, only the FSS match rate with QCAS (and its predecessor QCES) exceeds 20% (at 24.5%) with an average match rate of 16.2% across the various ONS business surveys. The average match rates between the ITS, SSS and DTS with the various ONS business surveys are 46.9%, 45.9% and 40.8% (respectively) - with the ABS match rates being the greatest for the ITS and DTS, and QCAS match rates being greatest for the SSS and FSS. Overall, the SSS has the greatest match rates with the ONS business surveys (save for the ABS). Thus, matching the individual CBI surveys to the IDBR allows for a greater wealth of analysis by combining the qualitative firm-level survey returns of the CBI with the quantitative firm-level data of ONS business surveys such as the ABS, QCAS and MBS - which in turn have good match rates with the CBI data.

Table 2.10: Match Rates between the CBI Dataset with the ONS Business Surveys

	ITS	**SSS**	**DTS**	**FSS**
ABS	50.4	43.8	47.0	15.2
QCAS	46.6	48.8	46.7	24.5
MBS	43.7	45.1	28.8	9.0

Note: Match rates are percentages to one decimal place. Column 1 (ITS) are the match rates for firms which have completed the Industrial Trends Survey only. Column 2 (SSS) are the match rates for firms which have completed the Service Sector Survey only. Column 3 (DTS) are the match rates for firms which have completed the Distributive Trades Survey only. Column 4 (FSS) are the match rates for firms which have completed the Financial Services Survey only. Each row corresponds to an ONS business survey. Row 1 (ABS) is the Annual Business Survey, with data available from 2008 to 2018. Row 2 (QCAS) is the Quarterly acquisitions and disposals of Capital Assets (including its predecessor), with data available from 2000Q1 to 2016Q1. Row 3 (MBS) is the Monthly Business Survey (including its predecessors), with data available from 2000M1 to 2018M9.

[33]Match rates correspond only to the years when the various ONS business surveys were conducted. Data for the ABS is from 2008 to 2018, for QCAS (and its QCES predecessor) from 2000Q1 to 2016Q1, for MBS from 2010M01 to 2018M09, for MPI from 2000M01 to 2009M09 and for MIDSS from 2000M01 to 2009M12.

2.6 Testing the Directional Accuracy of Firm Forecasts; an Illustrative Exercise using Matched Data

Firms are deemed rational if their expectation (regarding a particular variable) and corresponding actual outcome are not systematically different. Given that the CBI dataset contains ex-ante forecasts (as well as ex-post backcasts) it has previously been used to examine the rationality of expectation formation (see Section 2.1 for some examples). There are two options for testing rationality using the CBI dataset (and business tendency surveys in general). First, is to quantify the firm-level ex-ante forecasts to generate an industry-level expectation series. The resulting test of rationality is then implemented at the industry-level, comparing the newly quantified expectation series with actual industry-level outcomes from national statistics. Second, is to use the firm-level survey responses to examine rationality at the firm-level - an advantage of these disaggregate tests is that they capture micro-heterogeneity (Lui et al., 2011b).

Das et al. (1999) and Lui et al. (2011b) outline how to examine rationality using qualitative firm-level ex-ante forecasts - where the firm-level forecasts reflect either the mode, the α-quantile (such as the median when $\alpha = 0.5$) or the mean of the firm's subjective density forecast. Assuming the firm-level ex-ante forecast refers either to the mode or α-quantile of the firm's subjective density forecast, only the corresponding firm-level ex-post backcast is required. In this instance, the CBI dataset on its own is sufficient to examine rationality. However, if (as Das et al. (1999) argue is likely) the firm-level ex-ante forecast is the mean of the firm's subjective density forecast[34], then corresponding quantitative firm-level actual outcome data is needed. In this case, the CBI dataset alone is not sufficient to examine rationality.

Through the matching exercise of Section 2.5, firm-level ex-ante forecasts across a range of variables have been matched with their corresponding actual quantitative outcomes. Thus, using and extending the work of Das et al. (1999) and Lui et al. (2011b) disaggregate non-parametric tests of the directional accuracy of firm forecasts (to account for micro-heterogeneity) can be conducted, where the firm-level ex-ante forecast is the mean of the firm's subjective density forecast (the most likely interpretation of the firm survey responses according to Das et al. (1999)).

[34] In which case firms act as if minimising their squared forecast errors (Das et al., 1999).

2.6.1 Non-Parametric Tests Measuring the Directional Accuracy of Forecasts

Without loss of generality, for individual firm i in period t let $x_{i,t}$ be the variable of interest and $E_t(x_{i,t}) = {}_tx^e_{i,t}$ the corresponding latent, quantitative expected value of $x_{i,t}$ (formed at the beginning of period t)[35]. Each survey wave, individual firm i provides ${}_t\chi^e_{i,t} = j$ - their (qualitative) ex-ante forecast of $x_{i,t}$, where $j \in \{-1, 0, 1\}$ is the answer bin selected by the firm. The answer bins are "down" ($j = -1$), "same" ($j = 0$) and "up" ($j = 1$)[36]. Equation 2.1 formally defines ${}_t\chi^e_{i,t}$.

$$
{}_t\chi^e_{i,t} = \begin{cases} -1 & \text{if } -\infty < {}_tx^e_{i,t} \leq \Gamma_{i,-1,t} \\ 0 & \text{if } \Gamma_{i,-1,t} < {}_tx^e_{i,t} \leq \Gamma_{i,0,t} \\ 1 & \text{if } \Gamma_{i,0,t} < {}_tx^e_{i,t} \leq \infty \end{cases} \tag{2.1}
$$

where $\Gamma_{i,j,t}$ are the latent threshold values separating the answer bins - which are subjectively determined by the firm and can vary across firms and over time[37]. Thus, ${}_t\chi^e_{i,t} = -1$ if firms expect $x_{i,t}$ to go down (i.e. if $-\infty < {}_tx^e_{i,t} \leq \Gamma_{i,-1,t}$), ${}_t\chi^e_{i,t} = 0$ if firms expect $x_{i,t}$ to stay the same (i.e. if $\Gamma_{i,-1,t} < {}_tx^e_{i,t} \leq \Gamma_{i,0,t}$) and ${}_t\chi^e_{i,t} = 1$ if firms expect $x_{i,t}$ to go up (i.e. if $\Gamma_{i,0,t} < {}_tx^e_{i,t} \leq \infty$), zero otherwise.

For a rational firm, $x_{i,t}$ is drawn from the same distribution on which ${}_t\chi^e_{i,t}$ is based (Das et al. (1999)). Thus, the criterion for rationality (where the firm-level ex-ante forecast is the mean of the firm's subjective density forecast) is formally defined in Equation 2.2.

$$
E_t(x_{i,t} | {}_t\chi^e_{i,t} = j) \in (\Gamma_{i,j-1,t}, \Gamma_{i,j,t}) \tag{2.2}
$$

According to Equation 2.2, firms which have selected ${}_t\chi^e_{i,t} = j$ are rational if the mean of the distribution of (quantitative) outcomes is in answer bin j. Explicitly, the criterion for rationality for firms whose ex-ante forecasts are "down", "same" and "up" are given by Equation 2.2a, Equation 2.2b and Equation 2.2c (respectively).

$$
E_t(x_{i,t} | {}_t\chi^e_{i,t} = -1) \in (-\infty, \Gamma_{i,-1,t}) \tag{2.2a}
$$

$$
E_t(x_{i,t} | {}_t\chi^e_{i,t} = 0) \in (\Gamma_{i,-1,t}, \Gamma_{i,0,t}) \tag{2.2b}
$$

$$
E_t(x_{i,t} | {}_t\chi^e_{i,t} = 1) \in (\Gamma_{i,0,t}, \infty) \tag{2.2c}
$$

[35] The CBI survey wave for quarter t is conducted in the final and first two weeks of quarter $t-1$ and t, respectively. Therefore, the survey returns for quarter t (completed effectively at the beginning of quarter t) provide the firm-level ex-ante forecasts for quarter t.

[36] Or an equivalent categorical ordering system such as "more", "same" and "less".

[37] Following both Das et al. (1999) and Lui et al. (2011b), Equation 2.1 (trivially) assumes that $\Gamma_{i,-2,t} = -\infty$ and $\Gamma_{i,1,t} = \infty$.

For example, firms which have selected "up" (${}_t\chi^e_{i,t} = 1$) are rational if the mean of the distribution of (quantitative) outcomes ($x_{i,t}$) is in answer bin "up" (($\Gamma_{i,0,t}, \infty$)).

The answer bin thresholds, $\Gamma_{i,-1,t}$ and $\Gamma_{i,0,t}$, are formally defined in Equation 2.3 and Equation 2.4 (respectively).

$$\Gamma_{i,-1,t} = (1 - \gamma_{-1})x_{i,t-1} \tag{2.3}$$

$$\Gamma_{i,0,t} = (1 + \gamma_0)x_{i,t-1} \tag{2.4}$$

where γ_{-1} and γ_0 are the percentage movement of $x_{i,t-1}$ needed for the answer bin thresholds in Equation 2.2 to be crossed. γ_{-1} and γ_0 formally defined in Equation 2.5 and Equation 2.6 (respectively).

$$\gamma_{-1} = \frac{{}_t x^e_{i,t} - x_{i,t-1}}{x_{i,t-1}} \text{ such that } {}_t x^e_{i,t} < x_{i,t-1} \tag{2.5}$$

$$\gamma_0 = \frac{{}_t x^e_{i,t} - x_{i,t-1}}{x_{i,t-1}} \text{ such that } {}_t x^e_{i,t} > x_{i,t-1} \tag{2.6}$$

where $0 \leq \gamma_{-1}, \gamma_0 \leq 1$. Thus, γ_{-1} is the percentage movement in $x_{i,t-1}$ such that the latent, quantitative expected value of $x_{i,t}$ (${}_t x^e_{i,t}$) is less than $x_{i,t-1}$. Similarly, γ_0 is the percentage movement in $x_{i,t-1}$ such that the latent, quantitative expected value of $x_{i,t}$ (${}_t x^e_{i,t}$) is greater than $x_{i,t-1}$. Note that while γ_{-1} and γ_0 are time invariant and the same across firms, Γ_{-1} and Γ_0 are not (due to the changing nature of $x_{i,t-1}$).

Note that Equation 2.2 is not a direct test of the rationality of expectation formation. Instead it is a definition which facilitates a direct and reliable comparison of the firm's ex-ante survey forecasts with the corresponding realised actual outcome. Thus it is a necessary prerequisite for non-parametric tests measuring the directional accuracy of forecasts. Using Equation 2.2, a 3x3 contingency table (Table 2.11) can be constructed (for each year of the dataset) to compare the firm's ex-ante survey forecasts (${}_t\chi^e_{i,t}$) with the corresponding classification (k) of the quantitative outcome ($x_{i,t}$). Let $y_{(j,k)}$ (the observation in row j and column k of Table 2.11) be the number of firms which for ${}_t\chi^e_{i,t} = j$ and $x_{i,t}$ is classified as k - where $k = -1$ if $x_{i,t}$ actually decreased, $k = 0$ if $x_{i,t}$ actually stayed the same and $k = 1$ if $x_{i,t}$ actually increased. Let $y_{(j,.)}$ be the total number of firms with ${}_t\chi^e_{i,t} = j$ (i.e. the row total of row j), $y_{(.,k)}$ be the total number of firms where the actual outcome ($x_{i,t}$) is classified as k (i.e. the column total of column k) and $y_{(.,.)}$ be the total number of firms in Table 2.11.

Following Driver and Meade (2019), Table 2.11 is used to conduct two non-parametric tests measuring the directional accuracy of forecasts for each year of the data - namely, the Hanssen and Kuipers discriminant (τ_t) and the Pearson Chi-Square test statistic (X^2_t). The Hanssen and Kuipers discriminant[38] measures relative forecasting skill by comparing

[38] Also known as the Hanssen-Kuipers score, true skill statistic, Peirce's skill score, Gerrity's score and

Table 2.11: Contingency Table Comparing Ex-Ante Forecasts with Corresponding Actual Outcomes

			$x_{i,t}$		
		$k=-1$	$k=0$	$k=0$	
${}_t\chi^e_{i,t}$	$j=-1$	$y_{(-1,-1)}$	$y_{(-1,0)}$	$y_{(-1,1)}$	$y_{(-1,.)}$
	$j=0$	$y_{(0,-1)}$	$y_{(0,0)}$	$y_{(0,1)}$	$y_{(0,.)}$
	$j=1$	$y_{(1,-1)}$	$y_{(1,0)}$	$y_{(1,1)}$	$y_{(1,.)}$
		$y_{(.,-1)}$	$y_{(.,0)}$	$y_{(.,1)}$	$y_{(.,.)}$

Note: $y_{(j,k)}$ is the observation in row j and column k (i.e. the number of firms which for ${}_t\chi^e_{i,t}=j$ and $x_{i,t}$ is classified as k); $j=-1$ if ${}_t\chi^e_{i,t}$ is "down", $j=0$ if ${}_t\chi^e_{i,t}$ is "same" and $j=1$ if ${}_t\chi^e_{i,t}$ is "up"; $k=-1$ if $x_{i,t}$ actually decreased, $k=0$ if $x_{i,t}$ actually stayed the same and $k=1$ if $x_{i,t}$ actually increased; $y_{(j,.)}$ is the row total of row j (i.e. the total number of firms with ${}_t\chi^e_{i,t}=j$); $y_{(.,k)}$ is the column total of column k (i.e. the total number of firms where the actual outcome ($x_{i,t}$) is classified as k) and $y_{(.,.)}$ is the total number of firms.

the number of rational forecasts[39] (corrected for random guessing) with the perfect forecast counterfactual (Doswell et al., 1990; Allouche et al., 2006). Let $y^e_{(j,k)}$ be the expected value of the $(j,k)^{th}$ element of Table 2.11, formally defined in Equation 2.7.

$$y^e_{(j,k)} = \frac{(y_{(j,.)})(y_{(.,k)})}{y_{(.,.)}} \tag{2.7}$$

Let $\mu_{(j,k)}$ be the component of $y_{(j,k)}$ due to forecasting skill and not random guessing, formally defined in Equation 2.8.

$$\mu_{(j,k)} = y_{(j,k)} - y^e_{(j,k)} \tag{2.8}$$

Then the number of rational forecasts (corrected for random guessing) in period t is $tr(\mu_{(j,k)})_t$ (i.e. the trace of the matrix $\mu_{(j,k)}$).

Table 2.12 is the perfect forecast counterfactual contingency table, where $y^*_{(j,k)}$ is the observation in row j and column k. Off-diagonal elements are zero and the diagonal elements are such that when the actual outcome ($x_{i,t}$) is classified as k, the firm had forecast ${}_t\chi^e_{i,t}=j$ where $j=k$.

The expected value of the $(j,k)^{th}$ element of Table 2.12 ($y^{e^*}_{(j,k)}$) is formally defined in Equation 2.9.

$$y^{e^*}_{(j,k)} = \frac{(y^*_{(j,.)})(y^*_{(.,k)})}{y^*_{(.,.)}} \tag{2.9}$$

where $y^*_{(j,.)}$ is the row total of row j in Table 2.12, $y^*_{(.,k)}$ is the column total of column k in Table 2.12 and $y^*_{(.,.)}$ be the total number of firms in Table 2.12. The component of $y^*_{(j,k)}$ due to forecasting skill and not random guessing in the perfect forecast counterfactual

Youden's J statistic.

[39]Where rational firms are defined by the criterion in Equation 2.2.

Table 2.12: The Perfect Forecast Counterfactual Contingency Table

		$x_{i,t}$			
		$k=-1$	$k=0$	$k=0$	
${}_t\chi^e_{i,t}$	$j=-1$	$y_{(.,-1)}$	0	0	$y_{(.,-1)} = y_{(-1,.)}$
	$j=0$	0	$y_{(.,0)}$	0	$y_{(.,0)} = y_{(0,.)}$
	$j=1$	0	0	$y_{(.,1)}$	$y_{(.,1)} = y_{(1,.)}$
		$y_{(.,-1)}$	$y_{(.,0)}$	$y_{(.,1)}$	$y_{(.,.)}$

Note: $j=-1$ if ${}_t\chi^e_{i,t}$ is "down", $j=0$ if ${}_t\chi^e_{i,t}$ is "same" and $j=1$ if ${}_t\chi^e_{i,t}$ is "up"; $k=-1$ if $x_{i,t}$ actually decreased, $k=0$ if $x_{i,t}$ actually stayed the same and $k=1$ if $x_{i,t}$ actually increased; $y_{(j,.)}$ is the row total of row j (i.e. the total number of firms with ${}_t\chi^e_{i,t}=j$); $y_{(.,k)}$ is the column total of column k (i.e. the total number of firms where the actual outcome ($x_{i,t}$) is classified as k) and $y_{(.,.)}$ is the total number of firms.

($\mu^*_{(j,k)}$) is formally defined in Equation 2.10.

$$\mu^*_{(j,k)} = y^*_{(j,k)} - y^{e^*}_{(j,k)} \tag{2.10}$$

Then the number of rational forecasts (corrected for random guessing) in period t in the perfect forecast counterfactual is $tr(\mu^*_{(j,k)})_t$ (i.e. the trace of the matrix $\mu^*_{(j,k)}$).

The Hanssen and Kuipers discriminant for period t (τ_t) is formally defined in Equation 2.11.

$$\tau_t = \frac{tr(\mu_{(j,k)})_t}{tr(\mu^*_{(j,k)})_t} \tag{2.11}$$

where $-1 \leq \tau_t \leq 1$ - with $\tau_t = 0$ firm forecasts are random, $\tau_t > 0$ firm forecasts are better than random (if $\tau_t = 1$ firm forecasts are perfect) and $\tau_t < 0$ firm forecasts are worse than random (if $\tau_t = -1$ firm forecasts are entirely wrong). Thus, Equation 2.11 formally defines if firm forecasts are less than, equal to or better than random.

The Pearson Chi-Square test statistic (X^2_t) determines if there is an association between categorical variables. This is formally defined, for each year of the data, in Equation 2.12.

$$X^2_t = \sum_{\forall j} \sum_{\forall k} \frac{(\mu_{(j,k)})^2}{y^e_{(j,k)}} \tag{2.12}$$

with $(j-1)(k-1)$ degrees of freedom. In other words, Equation 2.12 is a non-parametric test measuring the directional accuracy of firm forecasts, by testing if there is an association between the firm's ex-ante survey forecasts (${}_t\chi^e_{i,t}$) and the corresponding classification (k) of the quantitative outcome ($x_{i,t}$) (Driver and Meade, 2019). The null hypothesis is that forecasts and actual outcomes in Table 2.11 are independent (i.e. there is no association between them). Thus, failing to reject the null hypothesis indicates firm forecasts have no value. The alternative hypothesis is that forecasts and actual outcomes in Table 2.11 are dependent. Rejecting the null hypothesis is evidence that forecasts have value, as forecasts are associated with actual outcomes[40].

2.6.2 Empirical Application

Implementing Equation 2.2 requires three sources of data. Data on actual firm-level quantitative outcomes ($x_{i,t}$) - in this instance taken from the Bureau van Dijk FAME company accounts dataset[41]. Data on the firm-level ex-ante forecasts (${}_t\chi^e_{i,t}$) is available from the CBI dataset for manufacturing and mining firms (ITS), service sector firms (SSS), distributive trades firms (DTS) and financial services firms (FSS). The matching exercise of Section 2.5 ensures $x_{i,t}$ is linked with ${}_t\chi^e_{i,t}$ for each firm i in period t. Data used to construct the answer bin thresholds ($(\Gamma_{i,-1,t}, \Gamma_{i,0,t})$) is provided by the Answering Practices Survey (APS)[42]. In contrast to this study, neither Das et al. (1999) nor Lui et al. (2011b) had quantitative measures of the answer bin thresholds - and could not directly use the Equation 2.2 rationality criterion.

The APS (conducted by the CBI between 2009 and 2014) is a questionnaire for participating firms of the ITS, SSS, DTS or FSS where respondents answer a series of questions regarding how they complete their designated survey - in particular by indicating how firms interpret the survey questions and potential answers[43]. Question 9b, 5a, 17 and 4b of the ITS, SSS, DTS and FSS APS (respectively) ask firms what range of movement they consider falling within the answer bin "same" - with answer categories "0%", "1%", "1-2%", "2-4%", "4-8%" and ">8%". The results are presented in Table 2.13 and show what (percentage) movement in ${}_tx^e_{i,t}$ is acceptable for them to say ${}_tx^e_{i,t}$ stayed the same. For example, 28% of firms in the ITS APS say if ${}_tx^e_{i,t}$ changed by 1-2% their ex-ante forecast would be "same" (i.e. ${}_t\chi^e_{i,t} = 0$). In other words, Table 2.13 shows the (percentage) movement in ${}_tx^e_{i,t}$ needed for firms to select ${}_t\chi^e_{i,t} = -1$ or ${}_t\chi^e_{i,t} = 1$, instead of ${}_t\chi^e_{i,t} = 0$. For example, 28% of firms in the ITS say if ${}_tx^e_{i,t}$ decreased or increased by more than 1-2% their ex-ante forecast would be "down" (i.e. ${}_t\chi^e_{i,t} = -1$) or "up" (i.e. ${}_t\chi^e_{i,t} = 1$), respectively. Thus, Table 2.13 provides quantitative values of γ_{-1} and γ_0 - namely 0.01, 0.02, 0.04 and 0.08[44]. Note that larger (tighter) answer bin thresholds, such as γ_{-1} and γ_0 equal to 0.08 (0.01), result in more (less) firms satisfying the rationality criterion of Equation 2.2, due to the greater (smaller) proportion of actual outcomes classified as "same"

[40]Note there is a negative correlation between τ_t and the p-values of X^2_t. Higher values of the former indicate better than random forecasts which correspond with their being an association between the ex-ante survey forecasts and actual outcomes (i.e. the latter is lower).

[41]All company accounts data is winsorised at the first and ninety-ninth percentile to remove the influence of outliers.

[42]See Appendix B for further details, including survey questions and responses.

[43]There is only one set of APS results for each survey type over the period 2009 to 2014. In 2013 186 firms completed the ITS APS, in 2012 120 firms completed the SSS APS, in 2014 85 firms completed the DTS APS and in 2009 55 firms completed the FSS APS.

[44]Taking the upper value of potential APS answer categories listed in Table 2.13.

$(k = 0)$[45]. However, with tighter answer bin thresholds the proportion of actual outcomes classified as "down" $(k = -1)$ and "up" $(k = 1)$ increase. While the total number of firms satisfying the rationality criterion is now smaller, more firms are satisfying the criterion in Equation 2.2a and Equation 2.2c.

Table 2.13: The Percentage Movement of $x_{i,t-1}$ Needed for the Answer Bin Thresholds to be Crossed

	ITS	**SSS**	**DTS**	**FSS**
0%	-	-	22	-
1%	12	6	36	0
1-2%	28	26	28	29
2-4%	34	26	8	42
4-8%	25	33	-	27
>8%	-	8	-	2
Don't Answer	-	-	5	-

Source: Question 9b, 5a, 17 and 4b of the ITS, SSS, DTS and FSS APS (respectively). Each asks firms what range of movement they consider falling within the answer bin "same". Answer categories are "0%", "1%", "1-2%", "2-4%", "4-8%" and ">8%". All figures in percent (rounded to nearest whole number). Note 1% of firms in the DTS select >4%.

Question 9c of the ITS APS asks firms if the (percentage) movement needed for firms to answer "down" (i.e. ${}_t\chi^e_{i,t} = -1$) is lower, the same or higher than the (percentage) movement necessary for them to answer "up" (i.e. ${}_t\chi^e_{i,t} = 1$). Results are presented in Table 2.14, with 92% of firms stating the (percentage) movement is the same. For example, only 3% of firms say the (percentage) movement in ${}_tx^e_{i,t}$ for them to select ${}_t\chi^e_{i,t} = -1$ is higher than for them to select ${}_t\chi^e_{i,t} = 1$. While Table 2.14 only covers firms in the ITS, it seems unlikely that a near unanimity of firms (92%) in one industry would be in contrast with firms in other industries. Thus this study assumes, based on the results in Table 2.14, that for all firms of the CBI dataset $\gamma_{-1} = \gamma_0$.

Table 2.14: Is γ_{-1} lower, the same or higher than γ_0?

	Lower	**Same**	**Higher**
ITS	4	92	3

Source: Question 9c of the ITS APS. Firms are asked if the movement necessary for them to answer "down" is lower, the same or higher than the movement necessary for them to answer "up". Answer categories are "lower", "same" and "higher". All figures in percent (rounded to nearest whole number). Note there is no equivalent question in the SSS, DTS or FSS APS.

[45] In other words, with larger (tighter) answer bins, more (less) firms satisfy Equation 2.2b.

2.6.2.1 Output

Question 8, 3a, 2a and 3a of the ITS, SSS, DTS and FSS (respectively) ask firms (excluding seasonal variations) what are the expected trends for the next three months with regard to the volume of production (ITS), volume of business (SSS and FSS) and volume of sales (DTS)[46]. The Bureau van Dijk FAME dataset provides actual quantified outcomes - in the form of turnover[47]. Figure 2.4a, Figure 2.5a, Figure 2.6a and Figure 2.7a plot the Hanssen and Kuipers discriminant (τ_t) for each value of γ_{-1} and γ_0 with respect to output forecasts and realised outcomes in the manufacturing and mining, service, distributive trades and financial services sector (respectively). Figure 2.4b, Figure 2.5b, Figure 2.6b and Figure 2.7b plot the p-values of the corresponding Pearson Chi-Square test (X_t^2) for the manufacturing and mining, service, distributive trades and financial services sector (respectively).

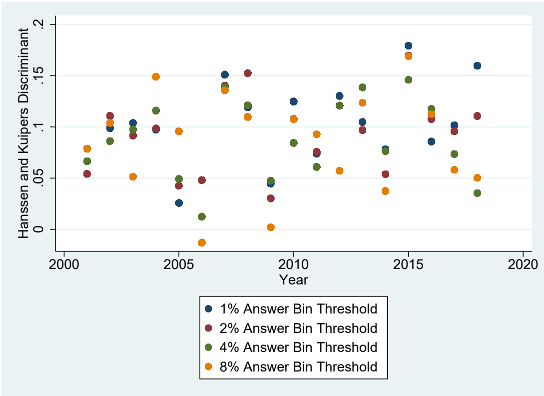
Figure 2.4a indicates that manufacturing and mining firms are (on the whole) better than random in forecasting output for each value of γ_{-1} and γ_0. There are periods where this is not true - notably 2006 and 2009 where firms' forecasts are effectively indiscriminate. While firms are better than random in their forecasting, they certainly do not make perfect forecasts. This is seen in column one of Table 2.15, which shows that the average Hanssen and Kuipers discriminant (τ_t) over the sample period for each value of γ_{-1} and γ_0 is only around 0.09 (0.1 in the case of the 1% answer bin threshold). However, Figure 2.4b shows that for the majority of years in the sample the Pearson Chi-Square test (X_t^2) null hypothesis is rejected (at the 5% statistical significance level), meaning there is an association between survey forecasts and realised outcomes. Thus, there is evidence of value regarding output forecasts in the manufacturing and mining sector. While column two of Table 2.15 shows the average Pearson Chi-Square test p-value is greater than 0.05, this is driven by outlier values in 2009 and 2006. Excluding these values the average average Pearson Chi-Square test p-value ranges from 0 to 0.02.

Firms in the service sector are hardly better than random in forecasting output (see Figure 2.5a, which graphs the Hanssen and Kuipers discriminant (τ_t) for each value of γ_{-1} and γ_0). The only exception to this general comment is 2007, where τ_t ranges from 0.24 to 0.31. Over the course of the sample, the average value of τ_t (for each value of γ_{-1} and γ_0) ranges from 0.07 to 0.11 (see Column one of Table 2.16). In addition, there is little evidence to support output forecasts have value (Figure 2.5b). The p-values of X_t^2 are predominately greater than 0.05 - thus, the null hypothesis that forecasts and actual

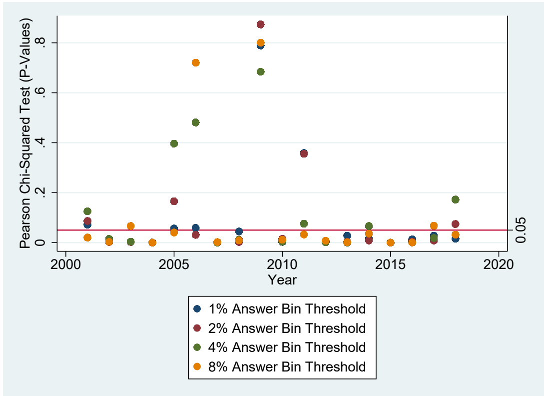
[46]These survey responses have been averaged over the year to make them compatible with company accounts data.

[47]While turnover is the sum of output and the first difference of finished goods, this approach follows Lui et al. (2011b) - when changes in turnover are not driven by stock they are driven by output. In addition, there are too many missing values for finished goods in the Bureau van Dijk FAME dataset to construct a company accounts output series.

Figure 2.4: The Accuracy of Directional Forecasts: Output and Manufacturing and Mining Firms



(a) Hanssen and Kuipers Discriminant (τ_t)



(b) Pearson Chi-Square Test (X_t^2) P-Values

Source: Question 8 of the Industrial Trends Survey (ITS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.15: Examining the Accuracy of Directional Output Forecasts in Manufacturing and Mining Firms

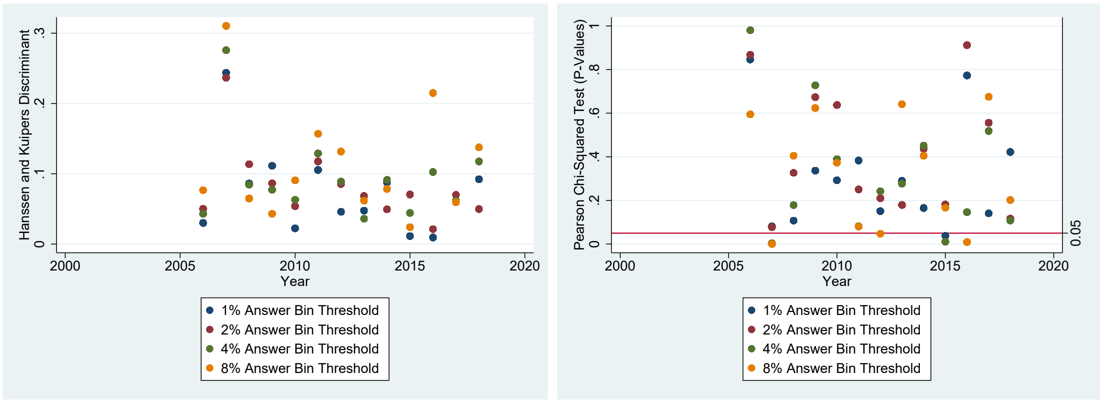
	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.1	0.08
$\gamma_{-1,0} = 0.02$	0.09	0.09
$\gamma_{-1,0} = 0.04$	0.09	0.12
$\gamma_{-1,0} = 0.08$	0.09	0.1

Source: Question 8 of the Industrial Trends Survey (ITS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

outcomes in the service sector are independent fails to be rejected (at the 5% statistical significance level). In fact, the average p-values of X_t^2 (for each value of γ_{-1} and γ_0 over the course of the sample) range from 0.31 to 0.43.

Firms in the distributive trades sector are better than random in forecasting output (for each value of γ_{-1} and γ_0) according to Figure 2.6a, with an average value of τ_t ranging from 0.2 to 0.22 (column one of Table 2.17). In fact, rarely does τ_t fall below 0.1, for any value of γ_{-1} and γ_0. The notable exception is 2004, where for γ_{-1} and γ_0 equal to 0.04 and 0.08 firms are slightly worse than random in forecasting. There is also considerable evidence in support of value in output forecasts for the distributive trades sector (Figure

Figure 2.5: The Accuracy of Directional Forecasts: Output and Service Firms



(a) Hanssen and Kuipers Discriminant (τ_t) (b) Pearson Chi-Square Test (X_t^2) P-Values

Source: question 3a of the Service Sector Survey (SSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.16: Examining the Accuracy of Directional Output Forecasts in Service Firms

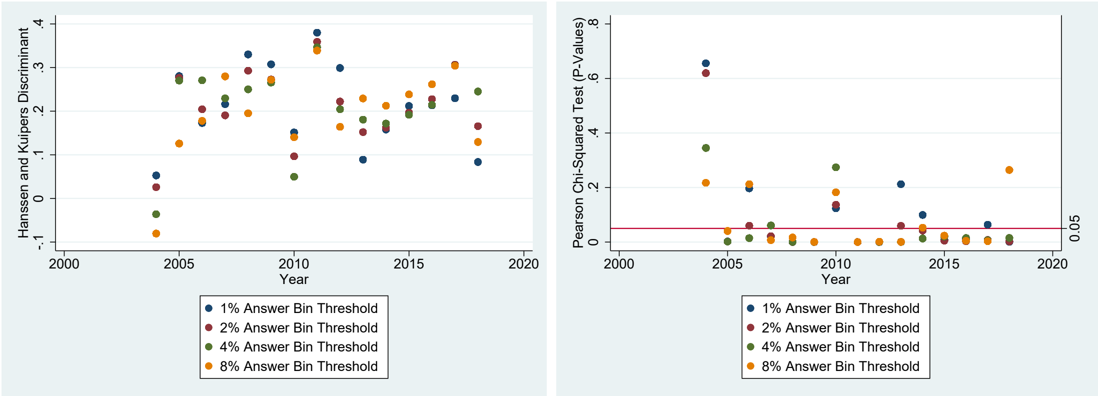
	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.07	0.31
$\gamma_{-1,0} = 0.02$	0.08	0.43
$\gamma_{-1,0} = 0.04$	0.09	0.31
$\gamma_{-1,0} = 0.08$	0.11	0.32

Source: Question 3a of the Service Sector Survey (SSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

2.6b). The rejection of the X_t^2 null hypothesis at the 5% significance level (as indicated by p-values less than 0.05) shows there is an association between the output forecasts and corresponding actual outcomes. While column two of Table 2.17 shows the average p-value of X_t^2 is greater than 0.05 (but less than 0.1 for γ_{-1} and γ_0 equal to 0.02, 0.04 and 0.08), this is largely due to the outlier values in 2004. Excluding these values the average average p-value of X_t^2 ranges from 0.03 to 0.05.

Similar to the service sector, financial services firms are (on the whole) indiscriminate in forecasting output for each value of γ_{-1} and γ_0 (Figure 2.7a). In fact, the average value of τ_t over the course of the sample doesn't exceed 0.05 for any value of γ_{-1} and γ_0 (column one Table 2.18). Furthermore, it is not uncommon for τ_t to be close to or less than zero -

Figure 2.6: The Accuracy of Directional Forecasts: Output and Distributive Trades Firms



(a) Hanssen and Kuipers Discriminant (τ_t) (b) Pearson Chi-Square Test (X_t^2) P-Values

Source: Question 2a of the Distributive Trades Survey (DTS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.17: Examining the Accuracy of Directional Output Forecasts in Distributive Trades Firms

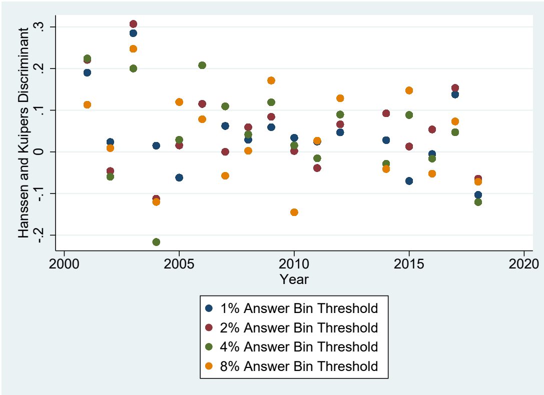
	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.22	0.1
$\gamma_{-1,0} = 0.02$	0.21	0.07
$\gamma_{-1,0} = 0.04$	0.21	0.06
$\gamma_{-1,0} = 0.08$	0.2	0.07

Source: Question 2a of the Distributive Trades Survey (DTS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

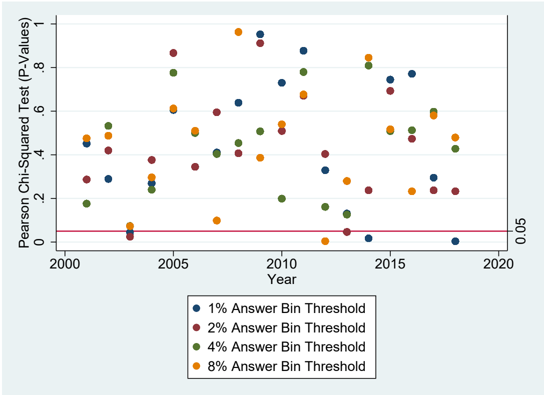
in some instances for every value of γ_{-1} and γ_0. Unsurprisingly, Figure 2.7b shows there is little evidence to support value in output forecasts. There are only a handful of instances where the p-values of X_t^2 are less than 0.05 - with average values ranging from 0.43 to 0.46 for each value of γ_{-1} and γ_0 over the course of the sample (column two of Table 2.18).

Thus, there is evidence output forecasts have value in both the manufacturing and mining and distributive trades sectors - but not in the service or financial services sectors. The two industries where there is evidence of forecast value are the two that produce a physical output. Specifically, firms in the manufacturing and mining sector produce a physical product from raw materials (inputs), while firms in the distributive trades sector purchase finished goods to sell to consumers. In contrast, firms in the service and financial services

Figure 2.7: The Accuracy of Directional Forecasts: Output and Financial Services Firms



(a) Hanssen and Kuipers Discriminant (τ_t)



(b) Pearson Chi-Square Test (X_t^2) P-Values

Source: Question 3a of the Financial Services Survey (FSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.18: Examining the Accuracy of Directional Output Forecasts in Financial Services Firms

	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.05	0.44
$\gamma_{-1,0} = 0.02$	0.05	0.43
$\gamma_{-1,0} = 0.04$	0.04	0.43
$\gamma_{-1,0} = 0.08$	0.04	0.46

Source: Question 3a of the Financial Services Survey (FSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

sector do not produce physical output (instead providing a service). There are greater costs with expectation errors for firms in the manufacturing and mining and distributive trades sectors, arising from the nature of their output. Unsold physical products (goods) depreciate or fall out of demand, becoming less valuable over time. Unsold physical products are costly to store and take space in warehouses and store fronts - space that could be used for other profitable items. Until the physical product is sold, the firm has money tied up in it - money that could be used for other profitable ventures. Firms can reduce their costs (through minimising these expectation error costs) by reducing systematic errors in expectation formation. Equally if firms do not produce enough physical product, this can result in lost custom as consumers switch to competitors. These additional costs (associated with physical output) are not relevant for the service or financial services sectors. Thus, their absence reduces the penalty incurred for having indiscriminate (or just slightly better) forecasts.

2.6.2.2 Employment

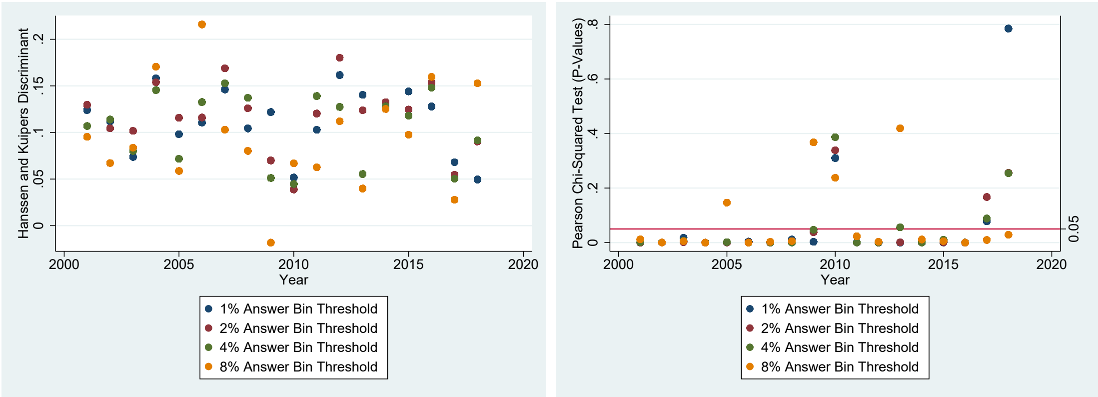
Question 6, 6, 7a and 6a of the ITS, SSS, DTS and FSS (respectively) ask firms (excluding seasonal variations) what are the expected trends for the next three months with regard to numbers employed. The Bureau van Dijk FAME dataset records actual (quantitative) numbers employed. Figure 2.8a, Figure 2.9a, Figure 2.10a and Figure 2.11a plot the Hanssen and Kuipers discriminant (τ_t) for each value of γ_{-1} and γ_0 with respect to employment forecasts and realised outcomes in the manufacturing and mining, service, distributive trades and financial services sector (respectively). Figure 2.8b, Figure 2.9b, Figure 2.10b and Figure 2.11b plot the p-values of the corresponding Pearson Chi-Square test (X_t^2) for the manufacturing and mining, service, distributive trades and financial services sector (respectively).

According to Figure 2.8a, firms in the manufacturing and mining sector are better than random in forecasting employment for each value of γ_{-1} and γ_0 - with average values of τ_t over the course of the sample ranging from 0.09 to 0.12 (column one of Table 2.19). Only in 2010 does τ_t fall below 0.05 for γ_{-1} and γ_0 equal to 0.02 and 0.04. Aside from this, only for γ_{-1} and γ_0 equal to 0.08 does τ_t fall below 0.05 - and then only in 2009, 2013 and 2017. In addition, Figure 2.8b shows there is considerable evidence to support value in employment forecasts - as in the majority of instances the p-value of X_t^2 is below 0.05. In other words, the null hypothesis of no association between employment forecasts and actual outcomes is rejected (at the 5% statistical significance level). On average, the X_t^2 p-value is less than 0.05 for γ_{-1} and γ_0 equal to 0.01, 0.02 and 0.04 (column two of Table 2.19).

On the whole, firms in the service sector are better than random in forecasting employment (Figure 2.9a) - with an average value of τ_t ranging from 0.11 to 0.14 for each value of γ_{-1} and γ_0 (column one of Table 2.20). Despite this Figure 2.9b does not provide considerable evidence of value in employment forecasts. In fact, the average p-value of X_t^2, for each value of γ_{-1} and γ_0, ranges from 0.14 to 0.2 (column two of Table 2.20). Thus, the null hypothesis of independence between employment forecasts and actual outcomes fails to be rejected.

Distributive trades firms are also better than random in forecasting employment (Figure 2.10a) - with average values of τ_t ranging from 0.16 to 0.19, for each value of γ_{-1} and γ_0 (column one of Table 2.21). Only in 2018 for γ_{-1} and γ_0 equal to 0.04 are firm

Figure 2.8: The Accuracy of Directional Forecasts: Employment and Manufacturing and Mining Firms



(a) Hanssen and Kuipers Discriminant (τ_t) (b) Pearson Chi-Square Test (X_t^2) P-Values

Source: Question 6 of the Industrial Trends Survey (ITS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.19: Examining the Accuracy of Directional Employment Forecasts in Manufacturing and Mining Firms

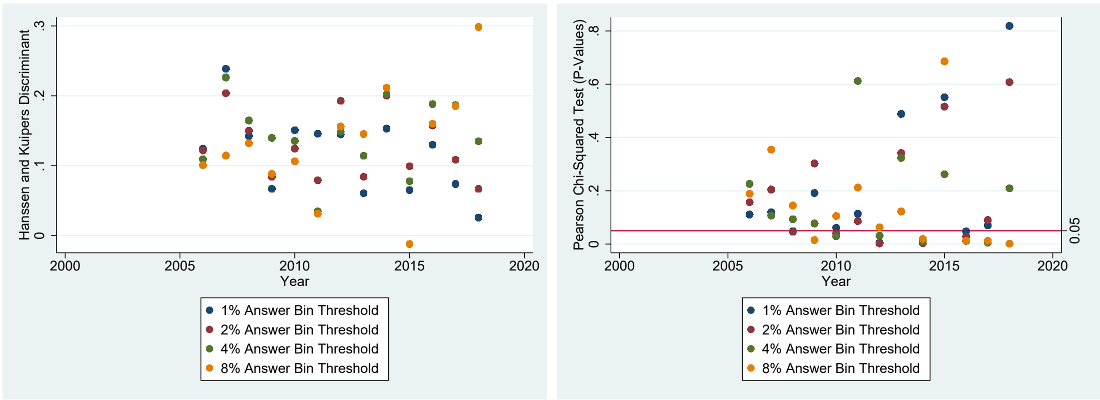
	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.11	0.048
$\gamma_{-1,0} = 0.02$	0.12	0.03
$\gamma_{-1,0} = 0.04$	0.11	0.04
$\gamma_{-1,0} = 0.08$	0.09	0.06

Source: Question 6 of the Industrial Trends Survey (ITS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

employment forecasts deemed indiscriminate. At the 5% statistical significance level, the X_t^2 null hypothesis is typically rejected for each value of γ_{-1} and γ_0 (Figure 2.10b). In fact, only in 2018 is the X_t^2 p-value greater than 0.05 for each value of γ_{-1} and γ_0 - with average X_t^2 p-values less than 0.05 for γ_{-1} and γ_0 equal to 0.04, and less than 0.1 for all other remaining values of γ_{-1} and γ_0 (column two Table 2.21).

As with the other industrial sectors, firms in the financial services sector also have better than random employment forecasts (Figure 2.11a) and have average values of τ_t ranging from 0.14 to 0.19 (column one of Table 2.22). Notably though, firm employment forecasts in 2010 and 2014 are at best indiscriminate and in some cases worse than random.

Figure 2.9: The Accuracy of Directional Forecasts: Employment and Service Firms



(a) Hanssen and Kuipers Discriminant (τ_t) (b) Pearson Chi-Square Test (X_t^2) P-Values

Source: Question 6 of the Service Sector Survey (SSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.20: Examining the Accuracy of Directional Employment Forecasts in Service Firms

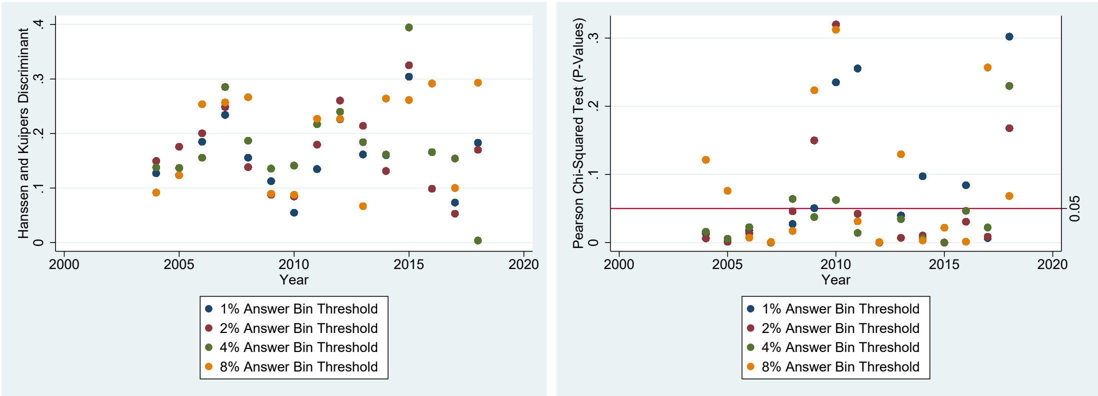
	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.11	0.2
$\gamma_{-1,0} = 0.02$	0.13	0.18
$\gamma_{-1,0} = 0.04$	0.14	0.15
$\gamma_{-1,0} = 0.08$	0.13	0.14

Source: Question 6 of the Service Sector Survey (SSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

However, the X_t^2 p-values (Figure 2.11b) do not provide evidence of value in employment forecasts - they are typically above 0.05 (indicating the null hypothesis is rejected at the 5% statistical significance level), with average values ranging from 0.14 to 0.22 (column two of Table 2.22).

Thus, there is evidence employment forecasts have value in both the manufacturing and mining and distributive trades sectors - but not in the service or financial services sectors. While this is similar to the conclusions regarding the value of output forecasts, it also reflects the different nature of employment in each of the industries. For example, firms providing a service may rely on part-time, shift-work, temporary workers, agency workers or gig workers more than firms producing physical output. Reliance on these types of

Figure 2.10: The Accuracy of Directional Forecasts: Employment and Distributive Trades Firms



(a) Hanssen and Kuipers Discriminant (τ_t) (b) Pearson Chi-Square Test (X_t^2) P-Values

Source: Question 7a of the Distributive Trades Survey (DTS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.21: Examining the Accuracy of Directional Employment Forecasts in Distributive Trades Firms

	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.16	0.07
$\gamma_{-1,0} = 0.02$	0.17	0.05
$\gamma_{-1,0} = 0.04$	0.18	0.03
$\gamma_{-1,0} = 0.08$	0.19	0.09

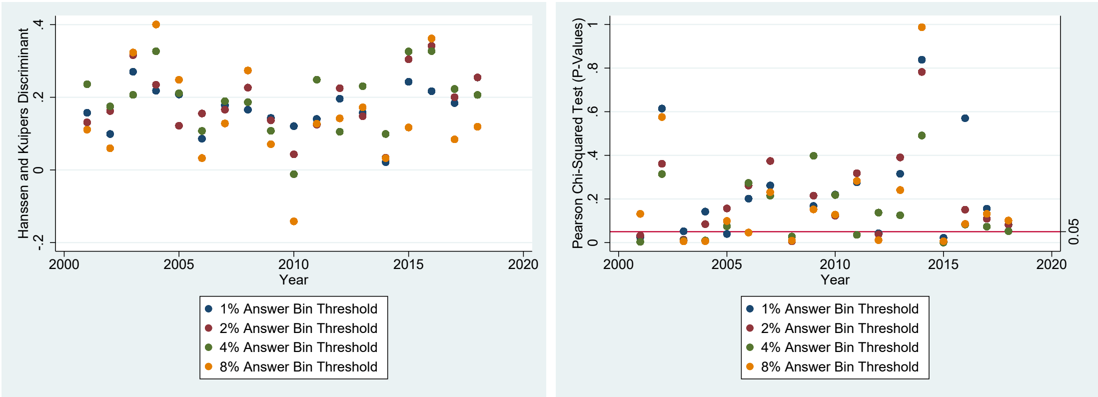
Source: Question 7a of the Distributive Trades Survey (DTS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

workers can make it more difficult to make better than random forecasts.

2.7 Conclusion

The CBI suite of business surveys is an excellent source of data regarding firms operating in the UK. It has an excellent panel structure (including both a substantial cross-section of firms over a significant time horizon) which also allows individual firm responses to be tracked over time. While the CBI dataset covers a wide range of important topics,

Figure 2.11: The Accuracy of Directional Forecasts: Employment and Financial Services Firms



(a) Hanssen and Kuipers Discriminant (τ_t) (b) Pearson Chi-Square Test (X_t^2) P-Values

Source: Question 6a of the Financial Services Survey (FSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. The 1% answer bin threshold is $\gamma_{-1,0} = 0.01$; the 2% answer bin threshold is $\gamma_{-1,0} = 0.02$; the 4% answer bin threshold is $\gamma_{-1,0} = 0.04$ and the 8% answer bin threshold is $\gamma_{-1,0} = 0.08$.

Table 2.22: Examining the Accuracy of Directional Employment Forecasts in Financial Services Firms

	Average τ_t	**Average X_t^2 p-value**
$\gamma_{-1,0} = 0.01$	0.17	0.22
$\gamma_{-1,0} = 0.02$	0.18	0.2
$\gamma_{-1,0} = 0.04$	0.19	0.14
$\gamma_{-1,0} = 0.08$	0.14	0.19

Source: Question 6a of the Financial Services Survey (FSS) and the Bureau van Dijk FAME dataset. The Hanssen and Kuipers Discriminant (τ_t) is defined in Equation 2.11. If $\tau_t \leq 0$ then firm forecasts are indiscriminate or worse, while if $\tau_t > 0$ then firm forecasts are better than random. The Pearson Chi-Square test statistic (X_t^2) is defined in Equation 2.12. The null hypothesis (no association between the categorical variables in Table 2.11) is rejected when the $p < 0.05$. Column one is the average value of τ_t, for each value of γ_{-1} and γ_0, over the course of the sample. Column two is the average p-value of X_t^2, for each value of γ_{-1} and γ_0, over the course of the sample. $\gamma_{-1,0} = 0.01$ is the 1% answer bin threshold; $\gamma_{-1,0} = 0.02$ is the 2% answer bin threshold; $\gamma_{-1,0} = 0.04$ is the 4% answer bin threshold and $\gamma_{-1,0} = 0.08$ is the 8% answer bin threshold.

the ability to match individual firm responses with company accounts data opens up the possibility of further areas of study. Match rates with the Bureau van Dijk FAME dataset and various ONS business surveys are reasonably good. An illustrative example of the benefits of matching the CBI dataset to company accounts data is provided by the exercise examining the directional accuracy of firm output and employment forecasts. The results indicate the output and employment forecasts of firms in the manufacturing and mining and distributive trades sectors have value. However, this is not the case in either the service or financial services sector.

Chapter 3

Output Expectations, Uncertainty and the UK Business Cycle: Evidence from the Confederation of British Industry's Suite of Business Surveys

3.1 Introduction

Expectation formation plays a key role in macroeconomics and increasing attention has been devoted to the way that individuals acquire and process information and the impact this has on output dynamics[1]. For example, existing literature has explored the role of learning and information rigidities in business cycle dynamics, attempted to distinguish the effects on output of news on fundamentals from sentiment and considered the role of psychological factors and cognitive limitations in output determination. At the same time, there has also been a related focus on the role of uncertainty as a potential source of business cycle fluctuations and/or a contributor to the propagation of innovations from other sources.

Given this interest, it is surprising that relatively little use is made of direct measures of expectations (taken from survey data) in modelling business cycle dynamics. Direct measures have been used to study the expectation formation process itself[2] and there are

[1]Lee et al. (2020b) is based on work contained in this chapter.
[2]For an overview see Pesaran and Weale (2006) and Croushore (2010).

measures of uncertainty which have been derived from survey responses (see, for example, Bachmann et al. (2013) and Arslan et al. (2015)). But few of the Vector Autoregression (VAR) models used to investigate the effect of uncertainty on output include direct measures of expectations in the VAR[3], and survey based measures of uncertainty are typically considered as just one among many alternative measures. Making insufficient use of survey data results in lost insight on firms' expectations, sentiments and uncertainties. In addition, the omission of direct expectation measures from business cycle analysis makes it difficult to distinguish the contributions to the cycle of firms' fundamentals and their use of information without employing potentially contentious identifying assumptions and can introduce model misspecification that obscures these behavioural insights.

This chapter constructs an industry-level quantified expected output growth, output disagreement and output uncertainty series using qualitative firm-level survey data (using the Confederation of British Industry (CBI) suite of business surveys), with the aim of analysing the impact of expected output and output uncertainty innovations on the UK economy - focusing on the manufacturing and mining, service and distributive trades sectors. This chapter adds to existing literature with two key contributions. First, it proposes a new and novel strategy for quantifying qualitative firm-level survey data which accounts for structural change. This is the meta-modelling quantification approach, which both theoretically and in practice yields enhanced industry-level quantified measures of expected output growth, output disagreement and output uncertainty (for the UK) compared to the simple balance statistic or the Anderson-Pesaran regression approach. Second, this chapter shows the effect of actually observed output uncertainty shocks on the UK economy in the immediate aftermath of the Great Financial Crisis (GFC). This is accomplished using a Beveridge-Nelson trends decomposition after constructing a four variable Cointegrated Vector Autoregression (CVAR) consisting of the newly quantified measures of output uncertainty, output disagreement and expected output growth along with actual output growth (available from official statistics).

The remainder of this chapter is organised as follows: Section 3.2 discusses relevant literature. Section 3.3 details how firm-level qualitative survey responses can be converted into an industry-level quantitative series. Section3.4 discusses the data used in this study. Section 3.5 implements the new meta-modelling quantification approach (as well as the simple balance statistic approach for comparison) to derive a quantified industry-level measure of expected output growth, output disagreement and output uncertainty. It also examines the appropriateness of using output disagreement as an output uncertainty proxy and compares the survey based output uncertainty proxy with others found in the literature. Section 3.6 utilises the quantified series to examine the dynamic inter-

[3]Aristidou et al. (2019) note that it is unusual to find direct measures of output expectations even in models that are used to forecast future output levels.

action between output uncertainty, output disagreement, expected output growth and actual output growth using a CVAR for the UK economy. This section concludes by constructing two Beveridge-Nelson trends to examine the effects of output uncertainty shocks actually observed on the UK economy in the immediate aftermath of the GFC. Section 3.7 concludes.

3.2 Literature Review

Previous academic literature has shown that uncertainty decreases firm-level investment, output, employment, consumer confidence and the stock market (Bloom et al., 2006; Bloom, 2009; Bekaert et al., 2013; Dennis and Kannan, 2013; Arslan et al., 2015; Jurado et al., 2015; Caldara et al., 2016; Girardi and Reuter, 2017). Denis and Kannan (2013) indicate that during the Great Recession the decline in industrial production was around a quarter greater than what it would have been in the absence of an uncertainty shock. Jurado et al. (2015) demonstrate at a twelve month horizon 29% of the forecast error variance in industrial production is accounted for by common macroeconomic uncertainty shocks. The September 2012 FOMC minutes explicitly note the (detrimental) role of uncertainty in consumer spending and firm investment decisions. Similarly, the Bank of England's Monetary Policy Committee has stated that high levels of uncertainty are likely to have negative impacts on the macroeconomy (Bank of England, 2013). Uncertainty is countercyclical and is higher during recessions for the US, Euro Area, UK, Canada and Japan (Bachmann et al., 2013; Jurado et al., 2015; Scotti, 2016)[4].

Bachmann et al. (2013), Jurado et al. (2015), Leduc and Liu (2016) and Girardi and Reuter (2017) argue that the effects of an increase in uncertainty are persistent. For example, Bachmann et al. (2013) and Girardi and Reuter (2017) argue the recovery of output is both long and slow. Leduc and Liu (2016) argue there is a persistent increase in unemployment and persistent decrease in inflation following an unexpected increase in uncertainty[5]. In fact, Leduc and Liu (2016) argue that the impact of an uncertainty shock is initially small and only over time it becomes substantially more consequential[6]. Denis and Kannan (2013) show that after an uncertainty shock the effect on industrial production and GDP dissipates after two and three years (respectively), while the effect on consumer confidence quickly reverses.

[4]Other periods of elevated uncertainty (outside of recessions) include 2004, 2005 and 2012 for the US; prior to and after the Great Recession and during the Greek Government Debt Crisis for the EA.

[5]Due to the persistent increase in unemployment and a persistent decrease in inflation, Leduc and Liu (2016) claim that uncertainty acts as a negative demand shock.

[6]With peak effects for unemployment and inflation occurring eighteen and twenty months from impact period (respectively).

Using a forecast error variance decomposition Bekaert et al. (2013) show that monetary policy shocks both increase uncertainty and are important drivers of uncertainty. A positive monetary policy shock has an immediate and negative impact on uncertainty while tighter monetary policy increases uncertainty (Bekaert et al., 2013). In addition, if a recession is found to be characterised by high levels of uncertainty then standard demand management policies have a smaller impact than normal as firms will most likely opt to wait and see (Bloom et al., 2011; Denis and Kannan, 2013). Thus, a policy stimulus needs to be sufficiently large to counteract the optimal behaviour of firms but also needs to be cancelled in sufficient time once uncertainty reverts to normal to avoid overshooting.

3.2.1 How to Measure Uncertainty

Uncertainty cannot be directly observed (or measured) as it relates to agents subjective beliefs. Instead uncertainty is indirectly measured using a proxy which (broadly speaking) can be classified into three categories: survey-based measures, financial-based measures and search-based measures. No one proxy is definitively accepted as the true measure of uncertainty.

3.2.1.1 Survey-Based Measures

Survey-based measures derive an uncertainty index either through utilising firm-level expectation errors (as in Bachmann et al. (2013) and Arslan et al. (2015)) or using the cross-section dispersion in firm responses (as in Bachmann et al. (2013) and Girardi and Reuter (2017)). The former creates an uncertainty index after constructing individual firm's expectation errors by comparing their ex-ante forecasts with their ex-post backcasts (assuming that heightened uncertainty increases the likelihood of firm expectation errors) (Bachmann et al, 2013; Arslan et al., 2015)[7]. This measure can return zero uncertainty - but only in the unlikely event that all firms make the same expectation error (Arslan et al., 2015).

The cross-section dispersion proxy operates by assuming heightened uncertainty coexists with greater disagreement among firms about the future time-path of the economy, whereas periods of low uncertainty are characterised by low disagreement (Bachmann et al., 2013; Girardi and Reuter, 2017). Greater cross-section dispersion of firm survey responses also reflects heterogeneity among firms and firm disagreement about future outcomes of the same variable - and is thus a potentially noisy uncertainty proxy (Andrade et

[7]Similarly, Jurado et al. (2015) and Scotti (2016) construct their respective measures of uncertainty using forecast errors (but not from survey-based measures). Jurado et al. (2015) creates an uncertainty index derived from the common volatility in the unforecastable component of a series of economic indicators. Scotti (2016) constructs a real-activity uncertainty index using market-based forecast errors.

al., 2016; Girardi and Reuter, 2017). In fact, Zarnowitz and Lambros (1987), Lahiri and Sheng (2010) and Rich and Tracy (2010) find at best inconclusive evidence and at worst negative evidence that cross-section dispersion is an appropriate proxy for uncertainty. However, contrasting evidence is provided by Bomberger (1996), Giordani and Söderlind (2003) and Bachmann et al. (2013). In particular, Bachmann et al. (2013) constructs both survey-based proxies and finds a high, positive correlation between them - arguing this removes firm heterogeneity as the driving force behind the cross-section dispersion measure. Similarly, by constructing the between-variance of the industrial subsectors of their cross-section dispersion measure the authors also show this uncertainty proxy is not been driven by firm disagreement.

3.2.1.2 Financial-Based Measures

Financial-based uncertainty measures rely on the realised volatility of stock market returns (for example the VIX). Examples of its use in the literature include Bloom (2009), Bekaert et al. (2013), Denis and Kannan (2013) and Leduc and Liu (2016). To be clear, the VIX is the option implied expected volatility on the S&P 500 index with a 30 calendar day horizon. In other words, the VIX represents the stock market option-based implied volatility (Bekaert et al., 2013). However, as finance-based measures can be influenced by external conditions they are also a noisy uncertainty proxy. In particular, the VIX is a noisy uncertainty proxy as it combines a true measure of uncertainty with stock market volatility (Jurado et al., 2015; Scotti, 2016). Furthermore, stock market volatility is driven largely by shocks other than that of uncertainty (Jurado et al., 2015).

3.2.1.3 Search-Based Measures

Search-based uncertainty measures derive an uncertainty proxy from newspaper articles and internet searches containing a set of keywords (such as uncertainty and economy), the number of provisions in the US tax code set to expire in future years and disagreement among economic forecasters (Baker et al., 2016). There are some criticisms of the Baker-Bloom-Davis uncertainty proxy. First, the choice of newspapers is arbitrary and lacks information on the weight economic agents place on the content of these articles. Second, the weighting system of the three components of this index is also arbitrary. Third, two of the three components of this index are determined by non-market participants.

3.2.1.4 Comparing the Uncertainty Proxies

Dennis and Kannan (2013) compare the effects of uncertainty on industrial production, GDP, unemployment and consumer confidence for the UK where uncertainty is measured by the implied volatility derived from options on the FTSE-100 index and the dispersion of one year ahead GDP forecasts. While both proxies yield the qualitatively predicted results, the proxy based on dispersion of GDP forecasts result in larger standard errors leading the authors to conclude that this particular uncertainty proxy does not have a significant impact on the UK economy (Dennis and Kannan, 2013). Jurado et al. (2015) compare their uncertainty index with proxies based on a stock market indicator, a GDP dispersion indicator, cross-section dispersion of firm profit growth, cross-section dispersion of firm stock and the cross-section dispersion of industry level of total factor productivity. The Jurado et al. (2015) indicator recognises only the 1973-1974 recession, 1981-1982 recession and the 2007-2009 Great Recession as periods of uncertainty. Moreover, these uncertainty episodes are larger, more persistent and more correlated with real activity compared to proxies based on cross-sectional dispersion (Jurado et al., 2015). Scotti (2016) compares their own uncertainty index based on real-activity with the VIX decomposition proxy of Bekaert et al. (2013), the Baker-Bloom-Davis proxy of Baker et al. (2016) and the Bachmann et al. (2013) cross-section dispersion index. The comparison confirms each uncertainty index is countercyclical and a decrease in employment occurs after an uncertainty shock. However, the speed and how deep the fall depends on the uncertainty proxy[8]. In addition, the correlations between the various indices range from 0.2 to 0.6 and the peaks of the differing uncertainty measures do not always coincide (Scotti, 2016).

The differences in the uncertainty proxies arise due to the differences in construction. For example, real-activity based uncertainty measures have a milder impact on economic activity compared to a finance-based measure (such as the VIX). This could reflect that the financial channel is key in the transmission of uncertainty shocks or that the VIX measures a different type of uncertainty or that the VIX is a noisy uncertainty measure (and is capturing more than just uncertainty). Thus the choice of uncertainty proxy determines what concept or type of uncertainty is being measured and which market participants are driving uncertainty.

[8]The Bekaert et al. (2013) uncertainty indicator is quickest to materialise and has the deepest trough while the Baker et al. (2016) and Bachmann et al. (2013) indicators record a lower impact.

3.3 Quantifying Qualitative Firm-Level Survey Data

Without loss of generality, quantification techniques are applied to firm-level survey responses related to output[9] and each survey round there exists a sample size of $N_{j,t}$ firms (for industrial sector j in period t), which can vary over time[10]. For ease of understanding, the relevant survey question takes the form of "do you expect output to increase, remain the same or decrease over the next three months (excluding seasonal variations)?". The quantification techniques employed here can be designated into two classifications. The first classification (Section 3.3.1) uses constant and symmetric quantification of firm survey responses. This approach has been employed by, for example, Bachmann et al. (2013) and Arslan et al. (2015). The second classification (Section 3.3.2) is the new and novel meta-modelling quantification approach which uses non-constant and non-symmetric quantification of firm survey responses. Both quantification techniques yield industry-level quantified measures of expected output growth, output disagreement and output uncertainty.

3.3.1 Constant and Symmetric Quantification

To begin, note that the firm survey response "same" is quantified as 0. Symmetric quantification assumes opposing firm survey responses are quantified by the same absolute number - in this case 1. In other words, when "up" is quantified as +1 then "down" is quantified as -1. Constant quantification assumes firm survey responses are always quantified by +/- 1 throughout the entire sample, irrespective of the economic environment. Here, +1 (-1) is the average percentage increase (decrease) in output for firms experiencing a rise (fall) in output.

3.3.1.1 The Simple Balance Statistic

The sample size for each survey ($N_{j,t}$) consists of all firms who report up ($u_{j,t} = \sum_{i=1}^{N} {}_t u^e_{i,j,t}$, i.e. $u_{j,t}$ is, for industrial sector j, the sum of each firm i's ex-ante forecast at the beginning of period t reporting they expect output to go up in period t), same ($s_{j,t} = \sum_{i=1}^{N} {}_t s^e_{i,j,t}$) and down ($d_{j,t} = \sum_{i=1}^{N} {}_t d^e_{i,j,t}$) for actual output growth ($y_{j,t}$). Accordingly, the sample size for each survey round is formally defined in Equation 3.1.

$$N_{j,t} = u_{j,t} + s_{j,t} + d_{j,t} = \sum_{i=1}^{N} {}_t u^e_{i,j,t} + \sum_{i=1}^{N} {}_t s^e_{i,j,t} + \sum_{i=1}^{N} {}_t d^e_{i,j,t} \tag{3.1}$$

[9]These quantification techniques can be applied to most qualitative survey questions.
[10]j is either the manufacturing and mining, service or distributive trades industrial sector.

Then expected output growth at the beginning of period t, as defined by the simple balance statistic $({}_t y^e_{R,j,t})$[11] [12], is given by Equation 3.2.

$$\begin{aligned} {}_t y^e_{R,j,t} &= (1)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_t u^e_{i,j,t} + (0)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_t s^e_{i,j,t} + (-1)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_t d^e_{i,j,t} \\ &= {}_t U^e_{j,t} - {}_t D^e_{j,t} \end{aligned} \tag{3.2}$$

where ${}_t U^e_{j,t} = \frac{1}{N_{j,t}}\sum_{i=1}^{N} {}_t u^e_{i,j,t}$ and ${}_t D^e_{j,t} = \frac{1}{N_{j,t}}\sum_{i=1}^{N} {}_t d^e_{i,j,t}$ are the proportion of firms at the beginning of period t who expect output to go up or go down in period t, respectively. Note the assumption of constant and symmetric quantification in Equation 3.2 is evident by the coefficients of ${}_t U^e_{j,t}$ and ${}_t D^e_{j,t}$ being +1 and -1, respectively.

3.3.1.2 The Simple Cross-Section Dispersion of Firm Responses

The cross-dispersion of firm responses is the corresponding second moment to Equation 3.2. To calculate this, first note Equation 3.3 and recall that $Var(X) = E(X^2) - E(X)^2$ with $SD(X) = \sqrt{Var(X)}$ for discrete random variable X with probability mass function $Pr(X = x)$:

$$\begin{aligned} ({}_t y^e_{R,j,t})^2 &= (1^2)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_t u^e_{i,j,t} + (0^2)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_t s^e_{i,j,t} + ((-1)^2)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_t d^e_{i,j,t} \\ &= {}_t U^e_{j,t} + {}_t D^e_{j,t} \end{aligned} \tag{3.3}$$

Then output disagreement at the beginning of period t, as defined by the simple cross-section dispersion of firm responses ($\sigma_{R,j,t}$), is given by Equation 3.4.

$$\sigma_{R,j,t} = \sqrt{{}_t U^e_{j,t} + {}_t D^e_{j,t} - ({}_t U^e_{j,t} - {}_t D^e_{j,t})^2} \tag{3.4}$$

Again the assumption of constant and symmetric quantification can be seen in the coefficients of ${}_t U^e_{j,t}$ and ${}_t D^e_{j,t}$ being +1 and -1, respectively.

[11] The subscript "R" - restricted - denotes constant and symmetric quantification. Subscript "A" - adjusted - denotes non-constant and non-symmetric quantification.

[12] The CBI survey wave for quarter t is conducted in the final and first two weeks of quarter $t-1$ and t, respectively. Therefore, the survey returns for quarter t (completed effectively at the beginning of quarter t) provide the firm-level ex-ante forecasts for quarter t and the firm-level ex-post backcasts for quarter $t-1$.

3.3.1.3 The Standard Deviation of the Simple Firm-Level Expectation Error Indicator Variable

If there exists both forward- and backward-looking questions regarding output then an indicator variable representing the simple firm-level expectation error can be constructed. In particular, this indicator variable is defined as the difference between the firm's ex-ante forecast and ex-post backcast. For example, if firms predict an output increase in t (quantified as +1) but in $t+1$ report output decreased in period t (quantified as -1) then the simple firm-level expectation error indicator variable is defined as 2, i.e. +1-(-1). Intuitively, the further removed the forecast and backcast are from one another the greater the indicator variable value (and thus the greater the quantification). The simple firm-level expectation error indicator variable for output in period t ($ee_{R,i,j,t}$) is formally defined in Equation 3.5:

$$ee_{R,i,j,t} = \begin{cases} 2 & \text{if } {}_{t+1}u_{i,j,t}|{}_t d^e_{i,j,t} \\ 1 & \text{if } {}_{t+1}u_{i,j,t}|{}_t s^e_{i,j,t} \text{ or } {}_{t+1}s_{i,j,t}|{}_t d^e_{i,j,t} \\ 0 & \text{if } {}_{t+1}u_{i,j,t}|{}_t u^e_{i,j,t} \text{ or } {}_{t+1}s_{i,j,t}|{}_t s^e_{i,j,t} \text{ or } {}_{t+1}d_{i,j,t}|{}_t d^e_{i,j,t} \\ -1 & \text{if } {}_{t+1}s_{i,j,t}|{}_t u^e_{i,j,t} \text{ or } {}_{t+1}d_{i,j,t}|{}_t s^e_{i,j,t} \\ -2 & \text{if } {}_{t+1}d_{i,j,t}|{}_t u^e_{i,j,t} \end{cases} \tag{3.5}$$

where ${}_{t+1}u_{i,j,t}$, ${}_{t+1}s_{i,j,t}$ and ${}_{t+1}d_{i,j,t}$ are the individual firm's ex-post backcast in period $t+1$ stating that in period t their output went up, stayed the same or went down (respectively). The standard deviation of Equation 3.5 yields a measure of output uncertainty for period t - reflecting uncertainty as the unforecastable component of a variable.

3.3.2 The Meta-Modelling Quantification Approach: Non-Constant and Non-Symmetric Quantification

An implication of assuming constant and symmetric quantification is that regardless if it is during the dot-com crisis, Great Moderation, Great Recession or during the Brexit negotiations, "up" and "down" are always quantified as +1 and -1 (respectively). Imposing constant and symmetric quantification implies the average percentage increase in output for firms experiencing a rise in their output equals (in absolute terms) the average percentage decrease in output for firms experiencing a fall in their output - and remain unchanged throughout the sample. There is no a priori reason for assuming this. In fact, it is expected that the average percentage increase in output (for firms experiencing a rise in their output) would exceed the average percentage decrease in output (for firms experiencing a fall in their output) during so-called "good times" (with the converse being true during "bad times"). In other words, the quantification of "up" should be larger than the quantification of "down" during good times - with the converse also being true. Simply put, constant and symmetric quantification fails to account for structural change.

Quantifying "up" as $+\alpha_j$, "same" as 0 and "down" as $-\beta_j$ for each industrial sector j, where $\alpha_j \neq \beta_j$ a priori, relaxes the symmetric quantification assumption. Now, $+\alpha_j$ ($-\beta_j$) is the average percentage increase (decrease) in output for firms experiencing a rise (fall) in their output. An estimate of α_j and β_j is obtained from regressing $y_{j,t}$ (industry-level actual output growth obtained from official statistics) on ${}_{t+1}U_{j,t}$ and ${}_{t+1}D_{j,t}$ (i.e. the proportion of firms in industrial sector j in period $t+1$ who reported their actual output did go "up" or "down" in period t, respectively). Thus, the estimation of α_j and β_j exploits the relationship between firm survey responses (in the form of the ex-post backcasts) and actual outcomes and uses this outcome to quantify the ex-ante forecasts (Pesaran, 1987). This is the Anderson-Pesaran regression approach[13].

The Anderson-Pesaran regression approach still imposes constant quantification. In other words, "up" and "down" are always quantified as $+\alpha_j$ and $-\beta_j$ (respectively) and do not alter as economic conditions alter. The constant quantification assumption can be relaxed by estimating a rolling regression of $y_{j,t}$ on ${}_{t+1}U_{j,t}$ and ${}_{t+1}D_{j,t}$ and quantifying "up" as $+\alpha_{j,t}$, "same" as 0 and "down" as $-\beta_{j,t}$. In particular using a fixed rolling window of τ periods, $y_{j,t}$ is regressed on ${}_{t+1}U_{j,t}$ and ${}_{t+1}D_{j,t}$ for period $[1, \tau]$ of the dataset, period $[2, \tau+1]$ of the dataset and so on until periods $[T-\tau+1, T]$ where T is the final period of the sample. By using a fixed window size the sample size in each regression remains constant while the coefficients from each regression are attributed (respectively) to period $\tau, \tau+1, ..., T$ - reflecting the value of new information revealed in the additional period in each rolling regression. Thus, structural change is only accounted for the in quantification process when the Anderson-Pesaran regression approach is combined with rolling estimates of the average percentage increase (decrease) in output, for firms experiencing a rise (fall) in their output.

As the choice of τ is arbitrary, specification uncertainty is introduced in estimating the average percentage increase (decrease) in output, for firms experiencing a rise (fall) in their output, as no (reasonable) value of τ is a priori preferential to any other. Furthermore, larger values of τ capture longer-run trends resulting in smoother series, while shorter values of τ generate series prone to sudden changes. Selecting one particular value of τ results in the measures of expected output growth, output disagreement and output uncertainty being potentially misspecified. This issue of specification uncertainty can be resolved by adopting the meta-modelling approach of Lee et al. (2015) and Aristidou et al. (2019), which is based on the Bayesian Model-Averaging formula in Hoeting et al.

[13]Note the simple balance statistic is a special case of the Anderson-Pesaran regression approach where $\alpha_j = \beta_j = 1$. See Appendix D.1 for an empirical application of the Anderson-Pesaran regression approach.

(1999). This meta-modelling quantification approach uses a set of rolling regressions of varying window size τ but at each point in time the data chooses the appropriate sample window (using a series of weights). A series of rolling regressions of $y_{j,t}$ on ${}_{t+1}U_{j,t}$ and ${}_{t+1}D_{j,t}$ for $\tau_{min} \leq \tau \leq \tau_{max}$ are conducted yielding estimates of $\alpha_{\tau,j,t}$ and $\beta_{\tau,j,t}$. For any quarter t there are at most $\tau_{max} - \tau_{min} + 1$ potential models defining the relationship between $y_{j,t}$ and the firm ex-post backcast[14].

The weights ($\omega_{\tau,j,t}$) applied to each model τ (i.e. the model with rolling window size τ) are updated each quarter t (using the predictive failure test of structural stability[15]) in order to best capture the relative relevance of each model describing new information. The predictive failure test of structural stability tests model τ successively against models $\tau - 1$ to τ_{min} and sequentially allocates weights downwards to models with smaller values of τ which outperform models with larger values of τ. Specifically, for any quarter t model τ is tested against model $\tau - 1$ under the null hypothesis of no structural break.

Failure to reject the null ensures the weight on model $\tau - 1$ in quarter $t - 1$ is assigned to model τ in quarter t. Model τ is now tested against model $\tau - 2$. If, however, the null is rejected then the weight of model $\tau - 1$ in quarter $t - 1$ is added to the weight of model $\tau - 1$ in quarter t and the weight on model τ in quarter t is set to 0. Model $\tau - 1$, with its updated weight, is now tested against $\tau - 2$. This is superior to simple averaging as it assigns weights to the models which best capture the relationship between $y_{j,t}$ and firm ex-post backcasts each period. In this manner, weights are dynamically selected each period based on the existence of structural breaks. Specifically, periods of stability see weights shifted to models with larger values of τ while weights are cascaded to models with smaller values of τ following structural breaks.

Equation 3.6 combines the updated meta-model weights $\omega_{\tau,j,t}$ with $\alpha_{\tau,j,t}$ and $\beta_{\tau,j,t}$ to obtain the meta-model average percentage increase (decrease) in output for firms experiencing a rise (fall) in their output.

$$\alpha_{meta,j,t} = \sum_{\tau=\tau_{min}}^{\tau_{max}} (\omega_{\tau,j,t})(\alpha_{\tau,j,t})$$

$$\beta_{meta,j,t} = \sum_{\tau=\tau_{min}}^{\tau_{max}} (\omega_{\tau,j,t})(\beta_{\tau,j,t}) \tag{3.6}$$

Now "up" is quantified as $+\alpha_{meta,j,t}$, "same" as 0 and "down" as $-\beta_{meta,j,t}$[16].

[14] This is obviously not true for the initial quarters of the sample where it is not feasible to have models with high values of τ. For example, in the ITS only one model of $\tau = 8$ is available for for 2001Q4 while two models ($\tau = 8$ and $\tau = 9$) are available for 2002Q1.

[15] Models with smaller values of τ are nested in models with larger values of τ.

[16] See Appendix D.1 for a plot of $+\alpha_{meta,j,t}$ and $-\beta_{meta,j,t}$ for each industrial sector, as well as a comparison with α_j and $-\beta_j$ from the Anderson-Pesaran regression approach and +/-1 from the balance

3.3.2.1 The Adjusted Balance Statistic

Using Equation 3.6 expected output growth at the beginning of period t, as defined by the adjusted balance statistic (${}_ty^e_{A,j,t}$), is given by Equation 3.7.

$$\begin{aligned} {}_ty^e_{A,j,t} &= (\alpha_{meta,j,t})\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_tu^e_{i,j,t} + (0)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_ts^e_{i,j,t} + (-\beta_{meta,j,t})\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_td^e_{i,j,t} \\ &= (\alpha_{meta,j,t})_tU^e_{j,t} - (\beta_{meta,j,t})_tD^e_{j,t} \end{aligned} \tag{3.7}$$

Equation 3.7 is the meta-modelling quantification approach counterpart to the simple balance statistic (Equation 3.2).

3.3.2.2 The Adjusted Cross-Section Dispersion of Firm Responses

To calculate the corresponding second moment of Equation 3.7 first note Equation 3.8.

$$\begin{aligned} ({}_ty^e_{A,j,t})^2 &= (\alpha^2_{meta,j,t})\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_tu^e_{i,j,t} + (0^2)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_ts^e_{i,j,t} \\ &+ ((-\beta_{meta,j,t})^2)\sum_{i=1}^{N}\frac{1}{N_{j,t}}{}_td^e_{i,j,t} \\ &= (\alpha^2_{meta,j,t})_tU^e_{j,t} + (\beta^2_{meta,j,t})_tD^e_{j,t} \end{aligned} \tag{3.8}$$

Then firm output disagreement at the beginning of period t, as defined by the adjusted cross-section dispersion of firm responses ($\sigma_{A,j,t}$), is given by Equation 3.9.

$$\sigma_{A,j,t} = \sqrt{(\alpha^2_{meta,j,t})_tU^e_{j,t} + (\beta^2_{meta,j,t})_tD^e_{j,t} - ((\alpha_{meta,j,t})_tU^e_{j,t} - (\beta_{meta,j,t})_tD^e_{j,t})^2} \tag{3.9}$$

Equation 3.9 is the meta-modelling quantification approach counterpart to the simple cross-section dispersion of firm responses (Equation 3.4).

3.3.2.3 ARCH Estimates of the Industry-Level Expectation Error

Given that the adjusted balance statistic (Equation 3.7) yields a theoretically more accurate measure of industry-level expected output growth than the simple balance statistic (Equation 3.2), it is now possible to construct a (reliable) quantitative measure of the industry-level expectation error. This is in contrast to the setup with constant and symmetric quantification, where the expectation error could only be identified through the

statistic

construction of an indicator variable[17]. Equation 3.10 formally defines the industry-level output expectation error in period t ($\epsilon\epsilon_{A,i,j,t}$):

$$\epsilon\epsilon_{j,t} = {}_t y^e_{A,j,t} - y_{j,t} \tag{3.10}$$

Therefore, positive values of $\epsilon\epsilon_{j,t}$ indicate overly optimistic firms as expectations exceed actualised values, while negative values of $\epsilon\epsilon_{j,t}$ indicate overly pessimistic firms underestimating actualised outcomes.

Following Lahiri and Sheng (2008) the ARCH(q_j) estimates of Equation 3.10, where q_j is determined by Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroscedasticity, creates a measure of output uncertainty for quarter t. In other words, output uncertainty in period t is measured as the conditional variance of Equation 3.10, formally defined in Equation 3.11:

$$\mu^2_{j,t} = \zeta_{j,0} + \zeta_{j,1}\varepsilon^2_{j,t-1} + ... + \zeta_{j,q}\varepsilon^2_{j,t-q} \tag{3.11}$$

where $\zeta_{j,1}, ..., \zeta_{j,q}$ are the ARCH parameters and $\varepsilon^2_{j,t-1}, ..., \varepsilon^2_{j,t-q}$ are the squared residuals from a regression of Equation 3.10 on it's intercept with $\varepsilon_{j,t} \sim N(0, \sigma^2_{j,t})$[18].

3.4 Data

There are two primary data sources for this chapter - the Office of National Statistics (ONS) (for official statistics) and the Confederation of British Industry (CBI) suite of business surveys (for firms-level survey responses). Industry-level actual output growth data is taken from ONS series L3BN, L3E2, and L2NE for the manufacturing and mining, service and distributive trades sectors (respectively).

The CBI dataset comprises the Industrial Trends Survey (ITS), the Service Sector Survey (SSS) and the Distributive Trades Survey (DTS) which cover the manufacturing and mining, service and distributive trades sectors (respectively)[19]. The ITS (the oldest survey) has been running since 1958 while the youngest survey (the SSS) started in 1998. These industrial sectors constitute more than 90% of UK private sector activity. Participation in survey waves is voluntary (not limited by CBI membership). While each survey is conducted monthly, once a quarter the CBI also conducts an enhanced survey with addi-

[17]Note that in this instance it is an industry-level expectation error which is being created, whereas Equation 3.5 is a firm-level measure. However, this distinction is minimal as the aim is to create an industry-level output uncertainty measure.

[18]Squaring Equation 3.10 also yields a measure of output uncertainty for period t. See Appendix D.2 for an empirical application of this method.

[19]The CBI also conducts the Financial Services Survey (FSS) - however this is excluded from this study as the sample of firms surveyed is smaller than the others.

tional questions. This study focuses on these quarterly survey waves. Collection for the survey published in month t begins around the final week of month $t-1$ with publication of results around the final week of month t. Thus firm-level survey responses for quarter t are collected at the very beginning of quarter t and provide forecasts for what firms expect in quarter t and backcasts for what happened in quarter $t-1$. In addition, to ensure continuity of survey respondents' only firms which have completed at least three consecutive survey waves are included in the sample. Survey data on ex-ante forecasts and ex-post backcasts for output is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). Specifically, firm-level survey responses are provided by Question 8, Question 3a and Question 2b of the ITS, SSS and DTS (respectively)[20]. There are a total of 2,158 (31,268), 479 (5,946) and 629 (9,650) participating firms (survey responses) in the ITS, SSS and DTS (respectively).

The proportion of firms (at the beginning of period t) who expect output to go up (${}_tU^e_{j,t}$) or go down (${}_tD^e_{j,t}$) in period t is plotted in Figure 3.1a to Figure 3.1c for each industrial sector j, along with the corresponding actual industry-level quarterly output growth. The broad co-movements in the data are apparent - with the proportions of firm reporting up and down increasing and decreasing as output increases and decreases. This is also evident in the correlations between actual output growth and the proportion of firms reporting up and down - which are (respectively) 0.43 and -0.54 for manufacturing and mining firms, 0.35 and -0.52 for service firms and 0.51 and -0.61 for distributive trades firms.

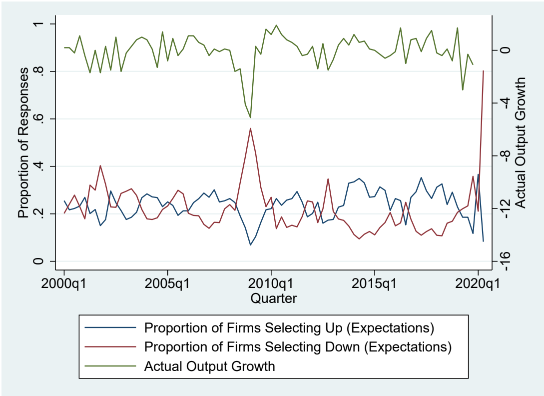
3.5 Expected Output Growth, Output Disagreement and Output Uncertainty in the UK

3.5.1 Expected Output Growth in the UK

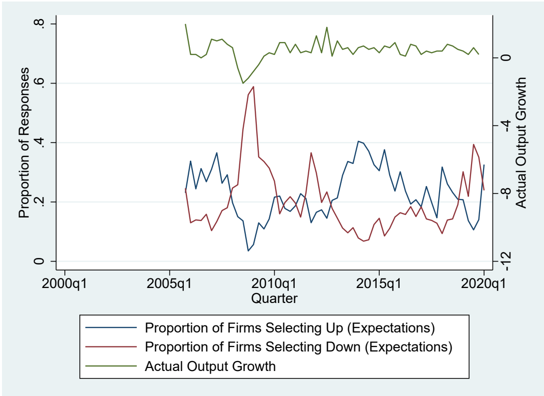
Figure 3.2a to Figure 3.2c plot (for each industrial sector j) expected output growth at the beginning of period t as defined by the simple balance statistic (Equation 3.2) alongside actual industry-level output growth. The correlations between ${}_ty^e_{R,j,t}$ and $y_{j,t}$ for each industrial sector are reasonably good: 0.51, 0.47 and 0.59 for the manufacturing and mining, service and distributive trades sectors (respectively). However, ${}_ty^e_{R,j,t}$ fails to closely track the movements of $y_{j,t}$ in any industrial sector. In particular, while the

[20] Output is referred to as volume of production, business and sales in the ITS, SSS and DTS (respectively).

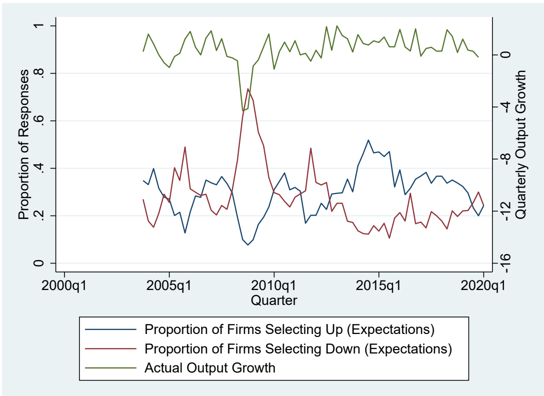
Figure 3.1: Actual Output Growth and Ex-Ante Survey Forecasts



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

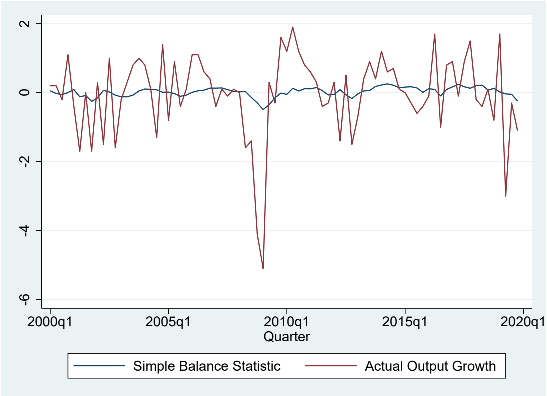
Note: Firm-level ex-ante survey forecasts are provided by Question 8, Question 3a and Question 2b of the ITS, SSS and DTS (respectively). Actual output growth data is taken from ONS series L3BN, L3E2, and L2NE for the manufacturing and mining, service and distributive trades sectors (respectively).

range of $y_{j,t}$ is 7, 3.5 and 6.52 (respectively) the corresponding range of ${}_ty^e_{R,j,t}$ is only 0.75, 0.86 and 1.05. The assumption of constant and symmetric quantification in Equation 3.2 ensures that ${}_ty^e_{R,j,t}$ only provides a general indicator of whether expected output growth is increasing or decreasing. For example, in each industrial sector the simple balance statistic records that expected output growth decreases during the Great Financial Crisis/Great Recession (GFC/GR) era but fails to record by how much. As such, it gives a qualitative indicator but not a quantitative one. Accordingly, Equation 3.2 should not be used to provide an accurate nowcast of $y_{j,t}$ for the UK manufacturing and mining, service and distributive trades sectors[21].

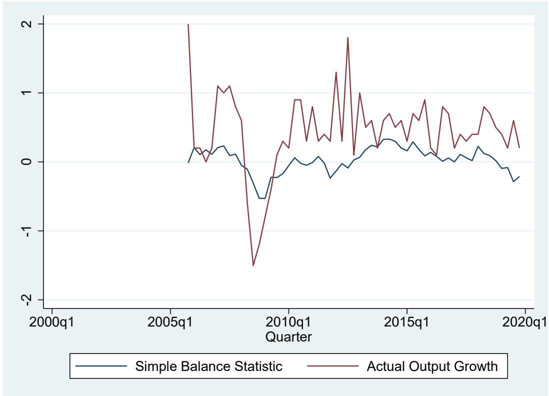
Figure 3.3a to Figure 3.3c plot (for each industrial sector j) expected output growth at the

[21]This outcome is not altered by weighting the simple balance statistic, as suggested in Pesaran (1987), to account for changing sample sizes each survey wave. In addition, while Pesaran (1987) and Pesaran and Weale (2006) argues that Equation 3.2 provides a useful expectations measure if the percentage change of ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are constant over the sample period this till leaves unresolved the fundamental issue with ${}_ty^e_{R,j,t}$ - the constant and symmetric quantification.

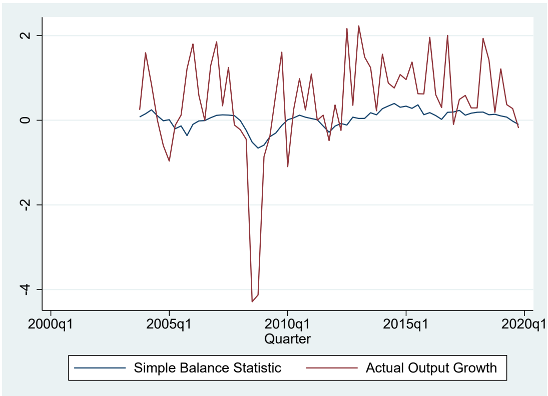
Figure 3.2: The Simple Balance Statistic and Actual Output Growth



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

Note: The simple balance statistic, at the beginning of period t, is defined for each industrial sector j as ${}_ty^e_{R,j,t} = {}_tU^e_{j,t} - {}_tD^e_{j,t}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t, respectively. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

beginning of period t as defined by the adjusted balance statistic (Equation 3.7) alongside actual industry-level output growth. The correlations between ${}_ty^e_{A,j,t}$ and $y_{j,t}$ for each industrial sector are very good and exceed their simple balance statistic counterparts: 0.65, 0.68 and 0.65 for the manufacturing and mining, service and distributive trades sectors (respectively). In addition, ${}_ty^e_{A,j,t}$ closely tracks the movements of $y_{j,t}$ in each industrial sector. This is confirmed by examining the ranges of the series - $y_{j,t}$ has a range of 7, 3.3 and 6.52, while ${}_ty^e_{A,j,t}$ has a range of 5.46, 2.58 and 4.44 for the manufacturing and mining, service and distributive trades sectors (respectively). References to expected output growth hereafter refer to the series generated by Equation 3.7, as it provides a reliable measure of industry-level expected output growth since it is both pro-cyclical and closely tracks the movements in $y_{j,t}$. For example, both in the manufacturing and mining and service sectors ${}_ty^e_{A,j,t}$ accurately captures the fall in $y_{j,t}$ during the GFC/GR era, while ${}_ty^e_{A,j,t}$ in the distributive trades sector makes a significant decrease as well. In fact, the GFC/GR era represents a period of extreme expectations[22]. In particular, expected output growth is classified as extreme between 2008Q4 to 2009Q2, 2008Q3 to 2009Q1 and 2008Q3 to 2009Q2 for the manufacturing and mining, service and distributive trades sectors respectively. In addition, expected output growth is classified as extreme in 2019Q4 (corresponding with ongoing Brexit negotiations and the UK general election) for the manufacturing and mining sector - the only sector with extreme expected output growth outside of the GFC/GR era[23].

Figure 3.4a to Figure 3.4c plot the difference in the time-varying parameters (i.e. $\alpha_{meta,j,t} - \beta_{meta,j,t}$) and the duration statistic ($DS_{j,t}$) that lie behind the expected output growth series generated by Equation 3.7. The duration statistic, defined in Equation 3.12, measures the average duration of the relationship between $y_{j,t}$ and firm ex-post backcasts each period - with breaks in the duration statistic representing structural breaks.

$$DS_{j,t} = \sum_{\tau=\tau_{min}}^{\tau_{max}} (\tau)(\omega_{\tau,j,t}) \tag{3.12}$$

Sudden changes in the difference in the time-varying parameters and breaks in the duration statistic correspond to known periods of economic change for each industrial sector. For example, note the time path of both series both before and after the GFC/GR era. Accordingly, the meta-modelling quantification approach accurately captures the time-varying nature of firm survey responses - providing further reassurance on the reliability of Equation 3.7 in generating an expected output growth series.

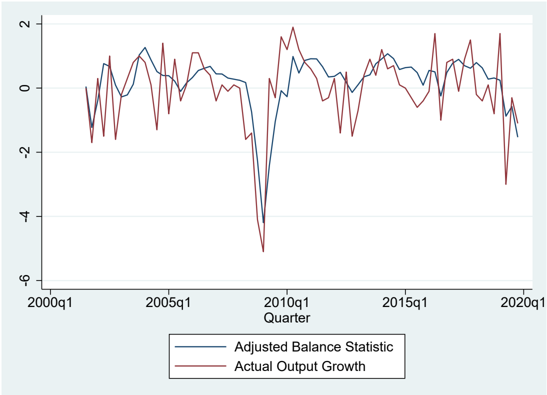
3.5.2 Output Disagreement in the UK

Figure 3.5a to Figure 3.5c plot, for each industrial sector j, output disagreement at the beginning of period t as defined by the simple cross-section dispersion of firm responses (Equation 3.4) alongside actual industry-level output growth. However, these quantified series are not satisfactory as the large oscillations in each series hinder the provision of any discernible information regarding industry-level output disagreement and actual output growth. Furthermore, only the manufacturing and mining $\sigma_{R,j,t}$ is countercyclical with $y_{j,t}$. The remaining measures of $\sigma_{R,j,t}$ are either acyclical or procyclical - the respective correlations are -0.16, 0.02 and 0.22 for the manufacturing and mining, service and

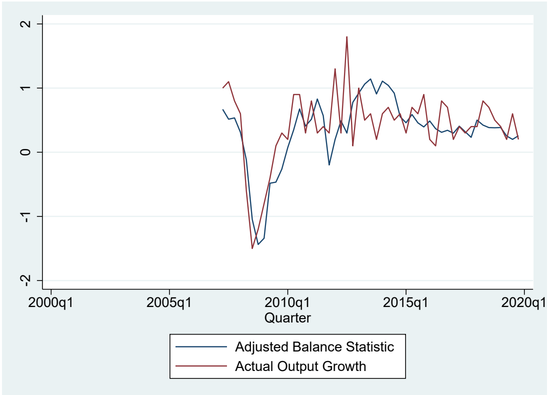
[22]Extreme expectations are defined as expectations 1.96 standard deviations above or below the mean. This corresponds to 5% two-tailed significance. See Bloom (2009) and Girardi and Reuter (2017).

[23]All of these extreme values are lower extreme values corresponding with substantial decreases in expected output growth - there are no upper extreme expected output growth values.

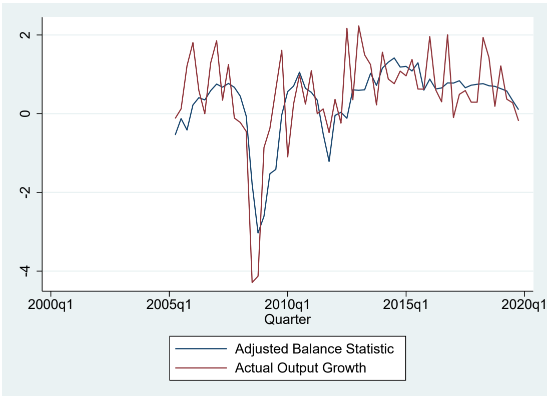
Figure 3.3: The Adjusted Balance Statistic and Actual Output Growth



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



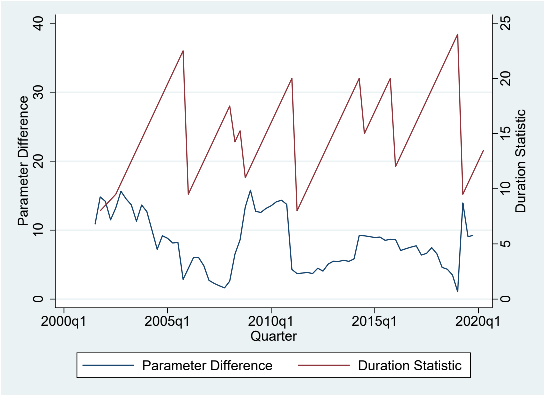
(c) Distributive Trades Sector Firms

Note: The meta-model adjusted balance statistic, at the beginning of period t, is defined for each industrial sector j as ${}_ty^e_{A,j,t} = (\alpha_{meta,j,t})_tU^e_{j,t} - (\beta_{meta,j,t})_tD^e_{j,t}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively), $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

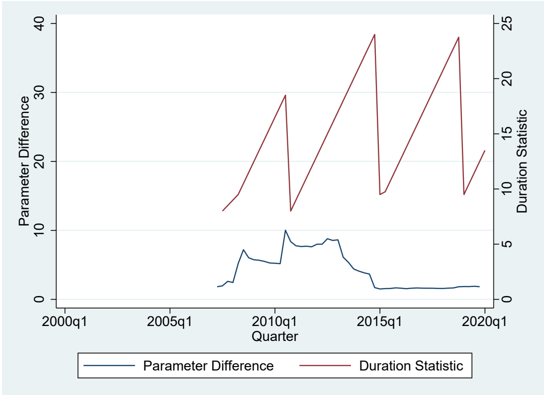
distributive trades sectors (respectively). Evidently, the imposition of constant and symmetric quantification in Equation 3.4 limits the ability of the resulting generated series to provide any insight into how industry-level output disagreement varies with the economic environment.

Figure 3.6a to Figure 3.6c plot, for each industrial sector j, output disagreement at the beginning of period t as defined by the adjusted cross-section dispersion of firm responses (Equation 3.9) alongside actual industry-level output growth. In each industrial sector $\sigma_{A,j,t}$ is countercyclical with $y_{j,t}$ with respective correlations of -0.19, -0.04 and -0.19 for the manufacturing and mining, service and distributive trades sectors (respectively).

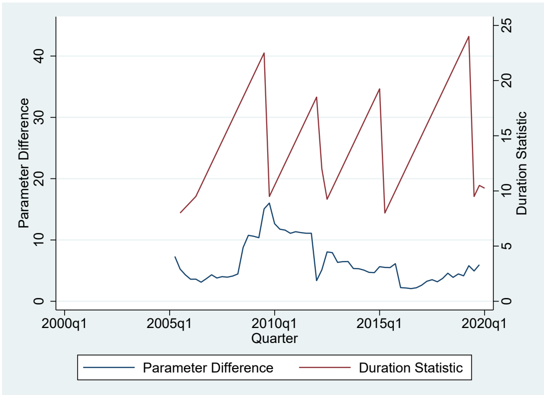
Figure 3.4: The Difference in Time-Varying Parameters and the Duration Statistic of the Meta-Modelling Quantification Approach



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



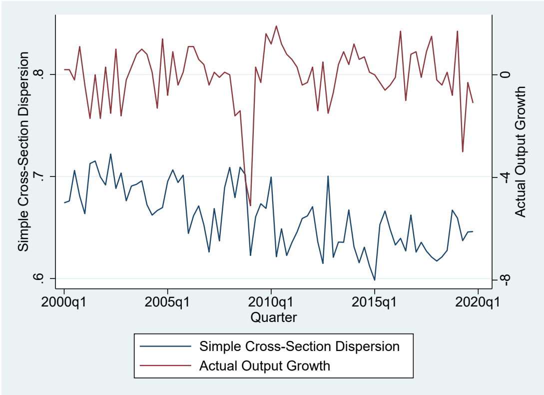
(c) Distributive Trades Sector Firms

Note: The difference in time-varying parameters is defined as $\alpha_{meta,j,t} - \beta_{meta,j,t}$ and the duration statistic is defined as $DS_{j,t} = \sum_{\tau=\tau_{min}}^{\tau_{max}} (\tau)(\omega_{\tau,j,t})$ for each industrial sector j where $\alpha_{meta,j,t} = \sum_{\tau=\tau_{min}}^{\tau_{max}} (\omega_{\tau,j,t})(\alpha_{\tau,j,t})$ is the meta-model average percentage increase in output for firms experiencing a rise in their output, $\beta_{meta,j,t} = \sum_{\tau=\tau_{min}}^{\tau_{max}} (\omega_{\tau,j,t})(\beta_{\tau,j,t})$ is the meta-model average percentage decrease in output for firms experiencing a fall in their output, τ is the fixed rolling regression window size and $\omega_{\tau,j,t}$ are the meta-model weights. Data sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

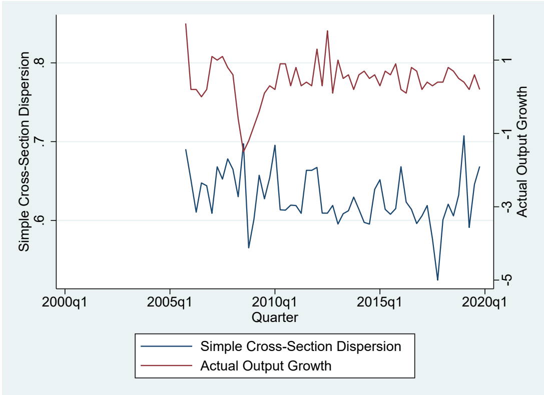
References to output disagreement hereafter refer to the series generated by Equation 3.9, as it provides a more reliable and realistic measure of industry-level output disagreement. For example, Figure 3.6a to Figure 3.6c depict $\sigma_{A,j,t}$ and $y_{j,t}$, showing heightened output disagreement around decreases in actual output growth (especially around the GFC/GR era). However not all periods of increasing output disagreement correspond to decreasing actual output growth. Periods of extreme output disagreement[24] vary across the industrial sectors. In the manufacturing and mining sector they occur in 2001Q4, 2002Q4 and

[24]Defined as output disagreement in exceeding 1.65 standard deviations of the mean. This corresponds to 5% one-tail significance.

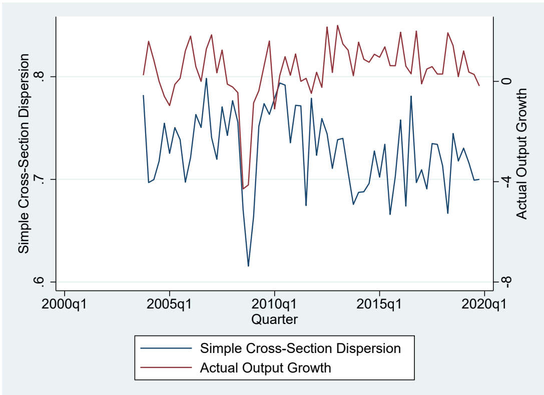
Figure 3.5: The Simple Cross-Section Dispersion of Firm Survey Responses and Actual Output Growth



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

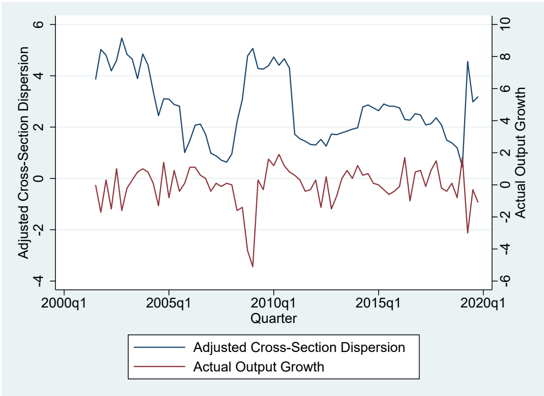
Note: The simple cross-section dispersion of firm survey responses, at the beginning of period t, is defined for each industrial sector j as $\sigma_{R,j,t} = \sqrt{{}_tU^e_{j,t} + {}_tD^e_{j,t} - ({}_tU^e_{j,t} - {}_tD^e_{j,t})^2}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t, respectively. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

2009Q1, in the service sector in 2010Q3 and 2012Q4 to 2013Q1 and in the distributive trades sector in 2009Q3 to 2010Q3. These all correspond to periods of economic turmoil - such as the aftermath of the dot-com crisis, the GFC or at the end of 2012 (as fears of a double-dip recession increased).

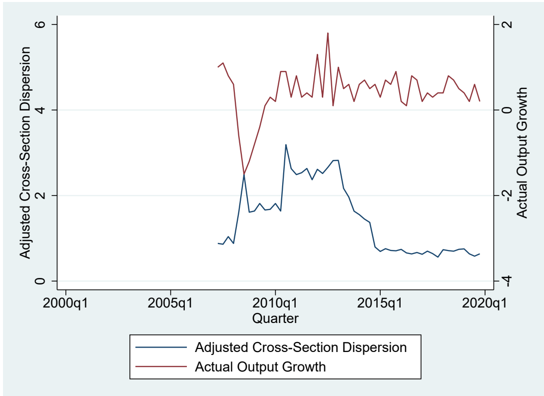
3.5.3 Output Uncertainty in the UK

Figure 3.7a to Figure 3.7c plot, for each industrial sector j, output uncertainty at the beginning of period t as defined by the standard deviation of Equation 3.5 alongside actual

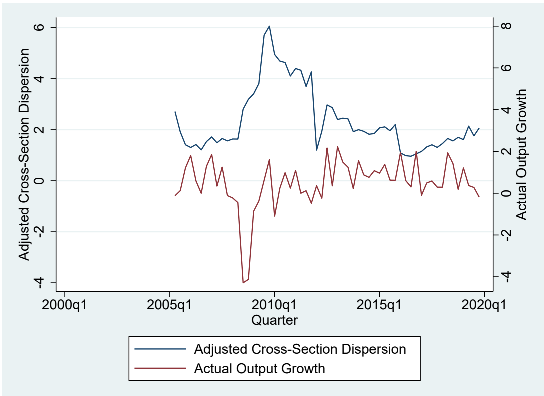
Figure 3.6: The Adjusted Cross-Section Dispersion of Firm Survey Responses and Actual Output Growth



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms

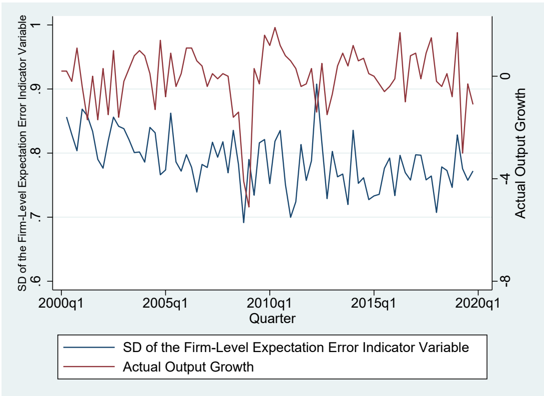


(c) Distributive Trades Sector Firms

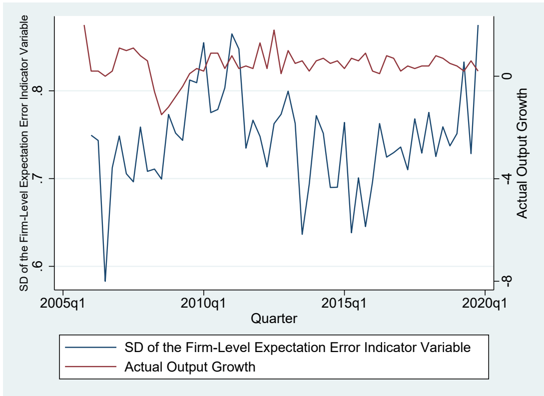
Note: The meta-model adjusted cross-section dispersion of firm survey responses, at the beginning of period t, is defined for each industrial sector j as $\sigma_{A,j,t} = \sqrt{(\alpha^2_{meta,j,t})_t U^e_{j,t} + (\beta^2_{meta,j,t})_t D^e_{j,t} - ((\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t})^2}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively), $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

industry-level output growth. However, these quantified series are not reliable measures of output uncertainty as the large oscillations in each series hinder the provision of any discernible information regarding industry-level output uncertainty and actual output growth. In addition, the correlation between the standard deviation of Equation 3.5 and $y_{j,t}$ for each industrial sector is at best weakly countercyclical - with respective correlations of 0.04, -0.01 and 0.15 for the manufacturing and mining, service and distributive trades sectors. Thus, imposing the assumption of constant and symmetric quantification limits the ability of the resulting generated series to provide any insight into how industry-level output uncertainty varies with the economic environment. Furthermore, this is an ex-post measure of output uncertainty - it involves the actual outcome which is unknown at the time expectations are formed. Thus, it does not properly capture the uncertainty surrounding the reported expectation at the time it was reported.

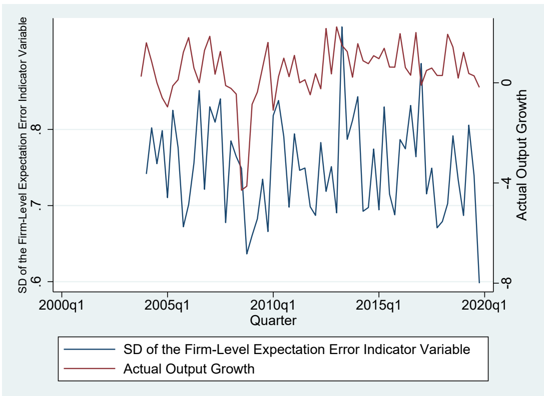
Figure 3.7: The Standard Deviation of the Firm-Level Expectation Error Indicator Variable and Actual Output Growth



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

Note: The simple firm-level expectation error indicator variable, at the beginning of period t, is defined for each industrial sector j as

$$ee_{R,i,j,t} = \begin{cases} 2 & \text{if } {}_{t+1}u_{i,j,t}|{}_t d^e_{i,j,t} \\ 1 & \text{if } {}_{t+1}u_{i,j,t}|{}_t s^e_{i,j,t} \text{ or } {}_{t+1}s_{i,j,t}|{}_t d^e_{i,j,t} \\ 0 & \text{if } {}_{t+1}u_{i,j,t}|{}_t u^e_{i,j,t} \text{ or } {}_{t+1}s_{i,j,t}|{}_t s^e_{i,j,t} \text{ or } {}_{t+1}d_{i,j,t}|{}_t d^e_{i,j,t} \\ -1 & \text{if } {}_{t+1}s_{i,j,t}|{}_t u^e_{i,j,t} \text{ or } {}_{t+1}d_{i,j,t}|{}_t s^e_{i,j,t} \\ -2 & \text{if } {}_{t+1}d_{i,j,t}|{}_t u^e_{i,j,t} \end{cases}$$

where ${}_{t+1}u_{i,j,t}$, ${}_{t+1}s_{i,j,t}$ and ${}_{t+1}d_{i,j,t}$ are the individual firm's ex-post backcast in period $t+1$ stating that in period t their output went up, stayed the same or went down (respectively). Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively).

Figure 3.8a to Figure 3.8c plot (for each industrial sector j) output uncertainty at the beginning of period t as defined by the ARCH(q_j) estimate of the industry-level expectation error (Equation 3.11) alongside actual industry-level output growth[25]. Figure 3.8a to Figure 3.8c indicate heightened output uncertainty around decreases in actual output growth. This is reinforced by the correlation between output uncertainty and actual output growth: -0.13, -0.1 and -0.37 for the manufacturing and mining, service and distributive trades sectors (respectively). Thus, the output uncertainty measure generated by the ARCH(q_j) estimate of Equation 3.10 is countercyclical - and is thus a more plausible and reliable measure of output uncertainty (compared to the standard deviation of Equation 3.5). Hereafter references to output uncertainty refer to the series generated by Equation 3.11. Extreme periods of output uncertainty occur in the manufacturing and mining sector in 2002Q3, 2009Q3 to 2009Q4 and 2019Q3, in the service sector in 2012Q2 and 2012Q4 and in the distributive trades sector in 2008Q4, 2009Q4, 2010Q2 and 2012Q4. Each of these extreme periods of output uncertainty occurred around times of economic turmoil - the dot-com crisis, the GFC, increased fears of a double dip recession towards the end of 2012 or the possibility of a no-deal Brexit in 2019.

3.5.4 Is Output Disagreement an Appropriate Output Uncertainty Proxy?

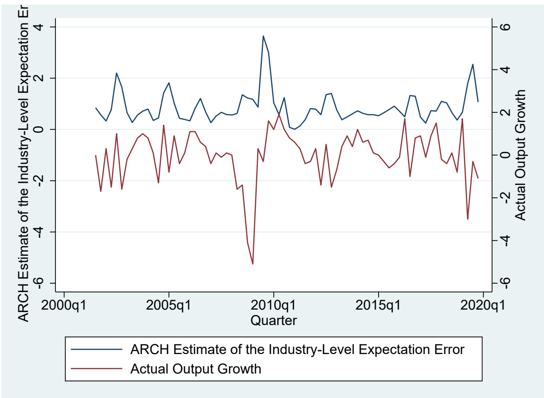
Output disagreement has been proposed as an output uncertainty proxy - notably by Bachmann et al. (2013). The key result which drives this conclusion is provided in Figure 3.9a to Figure 3.9c, which plots output disagreement (Equation 3.9) along with the standard deviation of Equation 3.13.

$$ee_{A,i,j,t} = \begin{cases} \alpha_{meta,j,t} + \beta_{meta,j,t} & \text{if } {}_{t+1}u_{i,j,t}|_t d^e_{i,j,t} \\ \alpha_{meta,j,t} & \text{if } {}_{t+1}u_{i,j,t}|_t s^e_{i,j,t} \\ \beta_{meta,j,t} & \text{if } {}_{t+1}s_{i,j,t}|_t d^e_{i,j,t} \\ 0 & \text{if } {}_{t+1}u_{i,j,t}|_t u^e_{i,j,t} \text{ or } {}_{t+1}s_{i,j,t}|_t s^e_{i,j,t} \text{ or } {}_{t+1}d_{i,j,t}|_t d^e_{i,j,t} \\ -\alpha_{meta,j,t} & \text{if } {}_{t+1}s_{i,j,t}|_t u^e_{i,j,t} \\ -\beta_{meta,j,t} & \text{if } {}_{t+1}d_{i,j,t}|_t s^e_{i,j,t} \\ -(\alpha_{meta,j,t} + \beta_{meta,j,t}) & \text{if } {}_{t+1}d_{i,j,t}|_t u^e_{i,j,t} \end{cases} \tag{3.13}$$

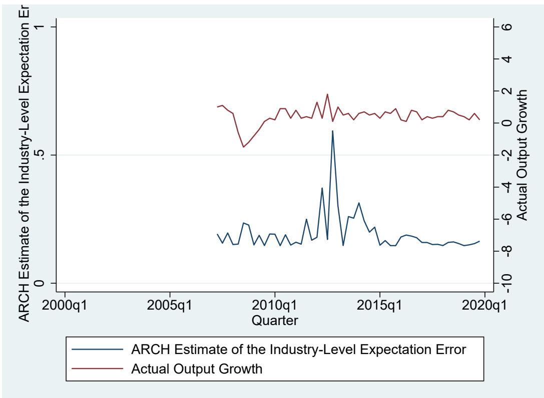
Equation 3.13 is the adjusted firm-level expectation error indicator variable, constructed using the meta-modelling quantification approach. Thus, it is the non-constant and non-symmetric equivalent of Equation 3.5. There is evidently a strong relation between the two time series - in fact, the correlation between the two series for each industrial sector

[25]Where q_j is 4, 1 and 1 for the respective industrial sectors

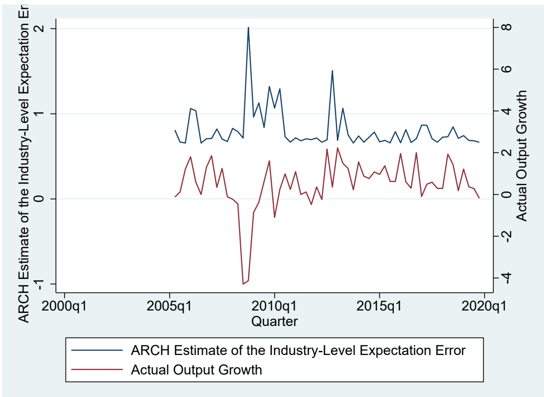
Figure 3.8: The ARCH Estimates of the Industry-Level Expectation Error and Actual Output Growth



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

Note: The ARCH(q) estimate of the quantitative meta-model expectation error, at the beginning of period t, is defined for each industrial sector j as $\mu^2_{j,t} = \zeta_{j,0} + \zeta_{j,1}\varepsilon^2_{j,t-1} + ... + \zeta_{j,q}\varepsilon^2_{j,t-q}$ where $\zeta_{j,1}, ..., \zeta_{j,q}$ are the ARCH parameters and $\varepsilon^2_{j,t-1}, ..., \varepsilon^2_{j,t-q}$ are the squared residuals from a regression of $\epsilon\epsilon_{j,t} = {}_t y^e_{A,j,t} - y_{j,t}$ on it's intercept where $\varepsilon_{j,t}\ N(0, \sigma^2_{j,t})$, $y_{j,t}$ is actual output growth and ${}_t y^e_{A,j,t} = (\alpha_{meta,j,t}) {}_t U^e_{j,t} - (\beta_{meta,j,t}) {}_t D^e_{j,t}$ is the meta-model adjusted balance statistic (i.e. expected output growth) with ${}_t U^e_{j,t}$ and ${}_t D^e_{j,t}$ as the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively), $\alpha_{meta,j,t}$ as the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ as the average percentage decrease in output for firms experiencing a fall in their output. Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroskedasticity selects lag length 4, 1 and 1 for the manufacturing and mining, service and distributive trades sectors (respectively). Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

j exceeds 0.9[26]. However, the standard deviation of Equation 3.13 (like the standard deviation of Equation 3.5) is an ex-post measure of output uncertainty - since it involves the actual (unknown) outcome at the time expectations are formed it does not properly

[26]Note the correlation between actual output growth and the standard deviation of Equation 3.13 is -0.13, 0.01 and -0.19 for the manufacturing and mining, service and distributive trades sectors (respectively).

capture the uncertainty surrounding the reported expectation at the time it was reported.

This does not necessarily refute the argument that output disagreement (Equation 3.9) is not a reliable output uncertainty proxy. In fact, output disagreement is both counter-cyclical with actual output growth and is an ex-ante measure - both important conditions for an output uncertainty proxy. Figure 3.10a to Figure 3.10c plots both output disagreement and output uncertainty for each industrial sector j - which reveals the different time paths between the series over the course of the sample. This is reflected by the correlation between output disagreement and output uncertainty - 0.34, 0.44 and 0.36 for the manufacturing and mining, service and distributive trades sectors (respectively). For example, while periods of heightened output uncertainty also result in heightened output disagreement the converse is not correct. Furthermore, output disagreement and output uncertainty have different extreme periods. Using output disagreement as an output uncertainty proxy would result in underestimating the level of output uncertainty (for example during 2009Q3 to 2009Q4 and 2019Q3 in the manufacturing and mining sector) and at other times exaggerating output uncertainty (for example in 2010Q3 in the service sector). In fact, both series also have different peaks. For example, in the manufacturing and mining sector output disagreement peaks during the dot-com period while output uncertainty peaks during the GFC/GR era. These discrepancies between the two time series reinforce the argument that the (adjusted) cross-section dispersion of firm responses is a noisy (and thus unreliable) output uncertainty proxy - since it captures firm disagreement, firm heterogeneity and uncertainty.

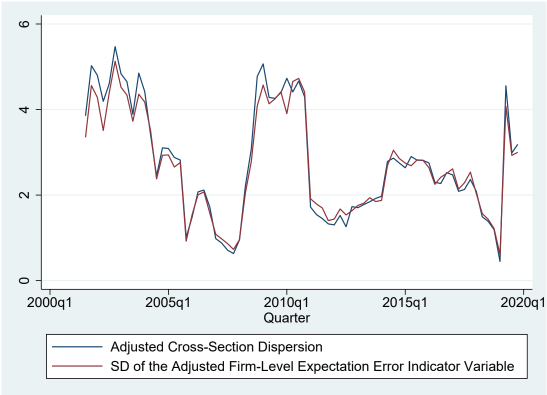
3.5.5 Comparing the Survey-Based Output Uncertainty with Alternative Measures

This subsection compares the survey-based output uncertainty with alternative proxies described in the literature: the standard deviation of total factor productivity, economic policy uncertainty and the VFTSE.

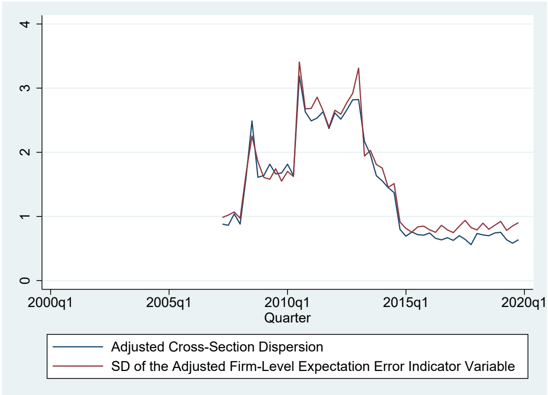
3.5.5.1 Standard Deviation of Total Factor Productivity

Data on the standard deviation of the total factor productivity is available from the ONS Multi-Factor Productivity dataset for the manufacturing and mining and service sectors. For example, an uncertainty proxy for the manufacturing and mining sector is constructed from the standard deviation of the total factor productivity of the CA, CB, CC, CD, CE, CF, CG, CH, CI, CJ, CK, CL and CM subsectors. The resulting uncertainty indices are presented in Figure 3.11a to Figure 3.11b. The only similarity between the standard

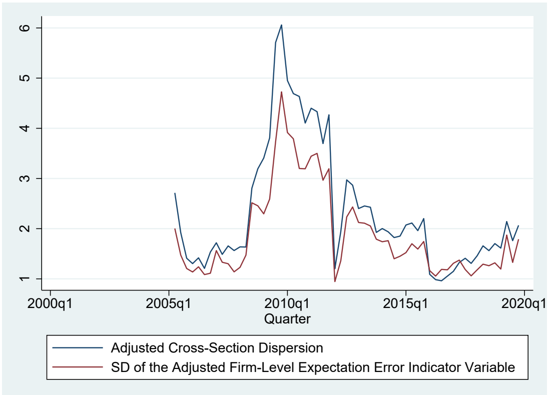
Figure 3.9: Comparing the Adjusted Cross-Section Dispersion of Firm Survey Responses with the Standard Deviation of the Adjusted Firm-Level Expectation Error Indicator Variable



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



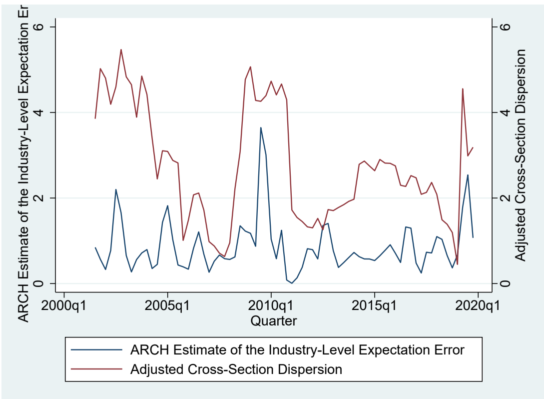
(c) Distributive Trades Sector Firms

Note: For each industrial sector j the adjusted cross-section dispersion of firm survey responses, at the beginning of period t, is defined as $\sigma_{R,j,t} = \sqrt{{}_tU^e_{j,t} + {}_tD^e_{j,t} - ({}_tU^e_{j,t} - {}_tD^e_{j,t})^2}$ and the adjusted firm-level expectation error indicator variable, at the beginning of period t, is defined as

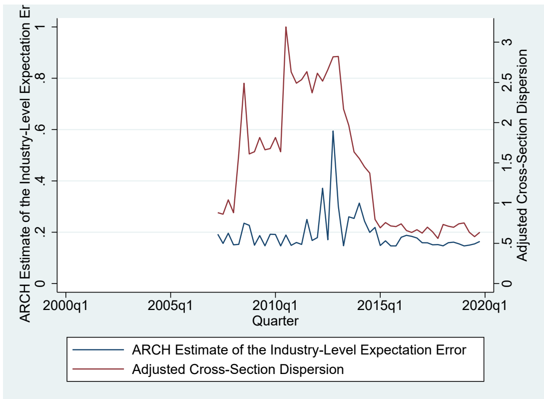
$$ee_{A,i,j,t} = \begin{cases} \alpha_{meta,j,t} + \beta_{meta,j,t} & \text{if } {}_{t+1}u_{i,j,t}|{}_td^e_{i,j,t} \\ \alpha_{meta,j,t} & \text{if } {}_{t+1}u_{i,j,t}|{}_ts^e_{i,j,t} \\ \beta_{meta,j,t} & \text{if } {}_{t+1}s_{i,j,t}|{}_td^e_{i,j,t} \\ 0 & \text{if } {}_{t+1}u_{i,j,t}|{}_tu^e_{i,j,t} \text{ or } {}_{t+1}s_{i,j,t}|{}_ts^e_{i,j,t} \text{ or } {}_{t+1}d_{i,j,t}|{}_td^e_{i,j,t} \\ -\alpha_{meta,j,t} & \text{if } {}_{t+1}s_{i,j,t}|{}_tu^e_{i,j,t} \\ -\beta_{meta,j,t} & \text{if } {}_{t+1}d_{i,j,t}|{}_ts^e_{i,j,t} \\ -(\alpha_{meta,j,t} + \beta_{meta,j,t}) & \text{if } {}_{t+1}d_{i,j,t}|{}_tu^e_{i,j,t} \end{cases}$$

where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively); ${}_{t+1}u_{i,j,t}$, ${}_{t+1}s_{i,j,t}$ and ${}_{t+1}d_{i,j,t}$ are the individual firm's ex-post backcast in period $t+1$ stating that in period t their output went up, stayed the same or went down (respectively) and $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

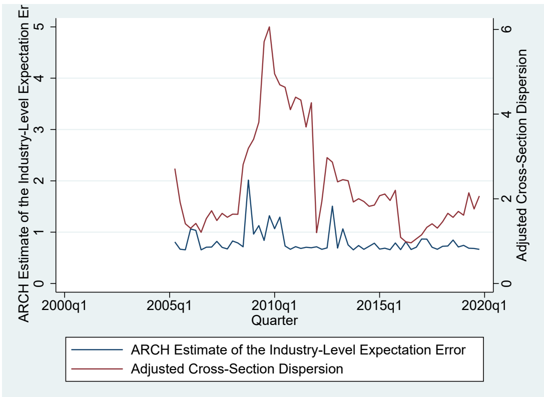
Figure 3.10: Comparing Output Disagreement and Output Uncertainty



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

Note: For each industrial sector j output disagreement (defined by the adjusted cross-section dispersion of firm survey responses) at the beginning of period t is $\sigma_{A,j,t} = \sqrt{(\alpha^2_{meta,j,t})_t U^e_{j,t} + (\beta^2_{meta,j,t})_t D^e_{j,t} - ((\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t})^2}$, output uncertainty (defined by the ARCH(q) estimate of the quantitative expectation error) at the beginning of period t is $\mu^2_{j,t} = \zeta_{j,0} + \zeta_{j,1}\varepsilon^2_{j,t-1} + ... + \zeta_{j,q}\varepsilon^2_{j,t-q}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively), $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output, $\zeta_{j,1}, ..., \zeta_{j,q}$ are the ARCH parameters, $\varepsilon^2_{j,t-1}, ..., \varepsilon^2_{j,t-q}$ are the squared residuals from a regression of $\epsilon\epsilon_{j,t} = {}_ty^e_{A,j,t} - y_{j,t}$ on it's intercept where $\varepsilon_{j,t}\ N(0, \sigma^2_{j,t})$, $y_{j,t}$ is actual output growth and ${}_ty^e_{A,j,t} = (\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t}$ is the meta-model adjusted balance statistic (i.e. expected output growth). Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroskedasticity selects lag length 4, 1 and 1 for the manufacturing and mining, service and distributive trades sectors (respectively). Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

deviation of total factor productivity and the survey-based output uncertainty is that each increases around the GFC/GR era. In the manufacturing and mining sector the standard deviation of total factor productivity does not record extreme uncertainty during either the dot-com period or 2019. Turning to the service sector, the standard deviation of total factor productivity posits uncertainty as initially falling, before rising and remaining fairly steady thereafter. This measure fails to capture the heightened period of extreme output uncertainty in 2012Q2 and 2012Q4. In contrast to the survey-based output uncertainty, the standard deviation of total factor productivity is not a direct measure of uncertainty.

Figure 3.11: Standard Deviation of Total Factor Productivity

(a) Standard Deviation of Total Factor Productivity (Manufacturing and Mining Sector Firms)

(b) Standard Deviation of Total Factor Productivity (Service Sector Firms)

Note: Data for total factor productivity is sourced from the Office of National Statistics (ONS) Multi-Factor Productivity for the manufacturing and mining and service sectors. Industrial subsectors included in the manufacturing and mining sector are CA, CB, CC, CD, CE, CF, CG, CH, CI, CJ, CK, CL and CM.

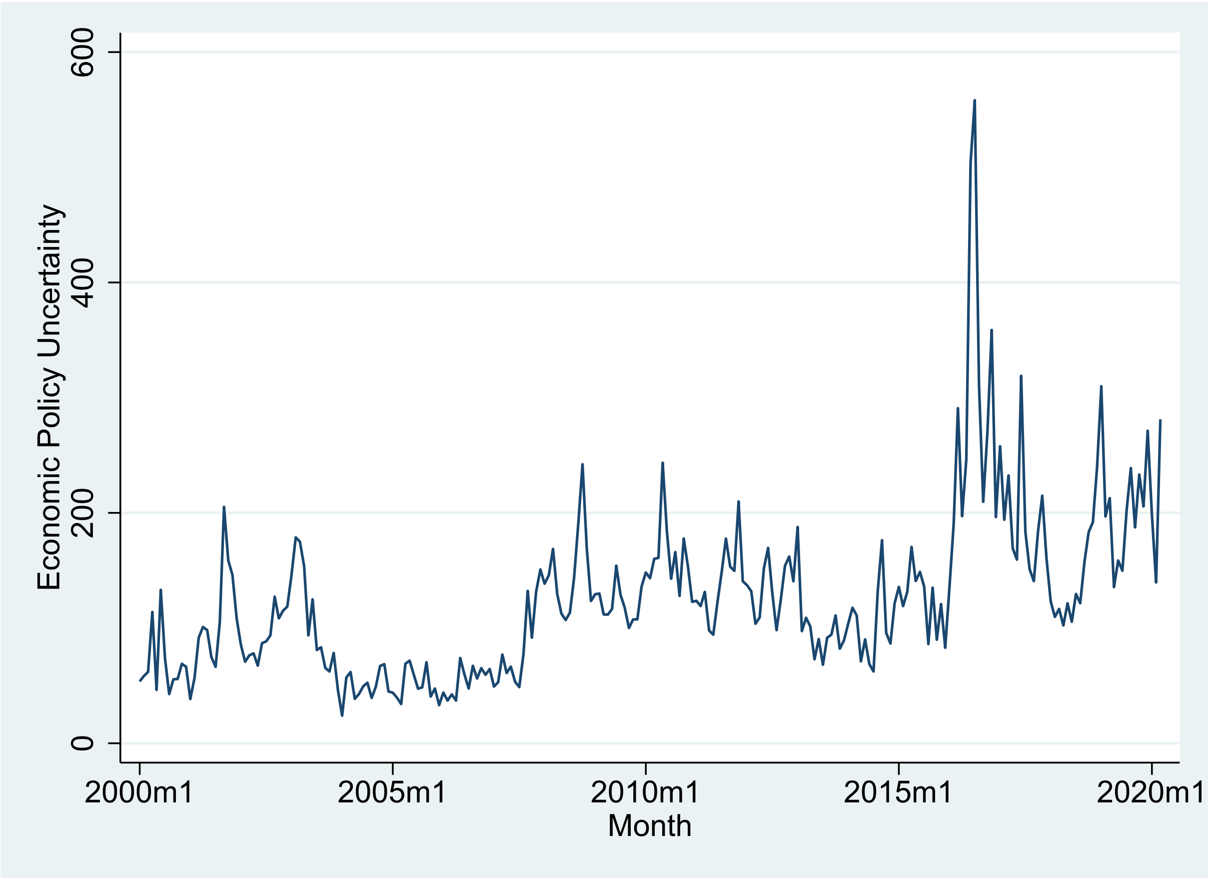
3.5.5.2 Economic Policy Uncertainty

The economic policy uncertainty index is created by using the number of articles in The Financial Times, The Times and Sunday Times, The Telegraph, The Daily Mail, The Daily Express, The Guardian, The Mirror, The Northern Echo, The Evening Standard, and The Sun containing the words “uncertain”, “uncertainty”, “economic”, “economy” in conjunction with “policy”, “tax”, “spending”, “regulation”, “Bank of England”, “budget” and “deficit”[27]. The resulting uncertainty index is plotted in Figure 3.12. This is not an industry specific proxy and as a result, it is unable to capture the differences in uncertainty across industrial sectors. There are (however) a number of recognisable trends in Figure 3.12 - an increase in uncertainty around 2003, decrease during the Great Moderation and increased uncertainty during the GFC/GR era, which remains elevated for a time. There are a number of differences with the survey-based output uncertainty: uncertainty around 2003 is more prominent, uncertainty remains elevated post-Great Recession, there is an extended period of extreme uncertainty for much of 2016 and part of 2017 (in the aftermath of the Brexit referendum) and the peak periods of uncertainty differ between the

[27]Monthly data for this index is available at https://www.policyuncertainty.com/uk_monthly.html

two proxies. However, these differences can be explained by what the proxies are trying to measure. The survey-based measure generates a measure of output uncertainty in three industrial sectors while Figure 3.12 is a more general, economic policy-based measure of uncertainty. In addition, the survey-based output uncertainty is a direct measure based on the responses of market participants while general, economic policy-based uncertainty is created by journalists (i.e. non-market participants).

Figure 3.12: Economic Policy Uncertainty



Note: Data for economic policy uncertainty is sourced from https://www.policyuncertainty.com/uk_monthly.html and is based on the number of articles in The Financial Times, The Times and Sunday Times, The Telegraph, The Daily Mail, The Daily Express, The Guardian, The Mirror, The Northern Echo, The Evening Standard, and The Sun containing the words "uncertain", "uncertainty", "economic", "economy" in conjunction with "policy", "tax", "spending", "regulation", "Bank of England", "budget" and "deficit".

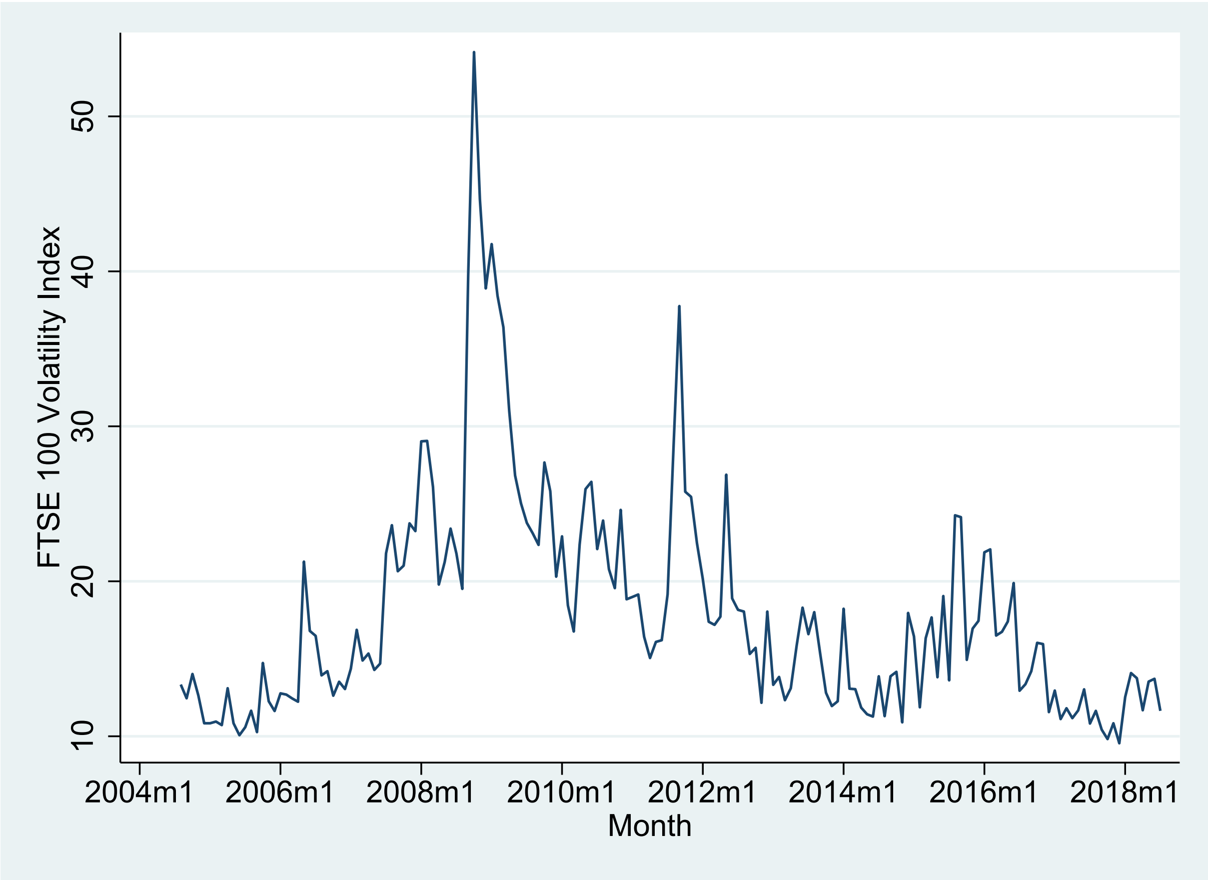
3.5.5.3 VFTSE

Figure 3.13 presents the FTSE 100 volatility index[28] - which is a finance-based uncertainty proxy starting in 2004M08 (until 2019M06). This proxy shows uncertainty was greatest during the GFC/GR era (which represents a period of extreme uncertainty, along with 2011M09), but in contrast to the survey-based output uncertainty the VFTSE was steadily

[28]Data available from https://uk.investing.com/indices/ftse-100-vix

increasing from 2005 onwards. However, this finance-based measure is a noisy uncertainty proxy as it reflects financial conditions as well as uncertainty.

Figure 3.13: FTSE 100 Volatility Index



Source: Data is available from https://uk.investing.com/indices/ftse-100-vix

3.6 Dynamic Interactions between Expected Output Growth, Output Disagreement, Output Uncertainty and Actual Output Growth in the UK

This section examines the dynamic interactions between expected output growth, output disagreement, output uncertainty and actual output growth in a vector autoregression (VAR) framework for each industrial sector j as in Equation 3.14.

$$X_{j,t} = \Phi_0 + \sum_{p=1}^{k} \Phi X_{j,t-p} + v_{j,t} \tag{3.14}$$

where $X_{j,t}$ is the vector of expected output growth, output disagreement, output uncertainty and actual output growth for industrial sector j, $\Phi_0, ..., \Phi_k$ are the matrices of parameters with lag-length $1 \leq p \leq k$ and $v_{j,t} \sim (0, \Theta)$ is the vector of shocks. Consistent estimates of the $\Phi_0, ..., \Phi_k$ are obtained using ordinary least squares, the variance-covariance matrix is estimated using fitted residuals and all shocks to industrial sector j are encapsulated by $v_{j,t}$. The impulse responses from shocks to the system are obtained by imposing a Cholesky decomposition. This imposes a causal ordering of the variables of $X_{j,t}$, where the variable ordered first is affected only by its own innovation (which in turn contemporaneously affects all other variables of $X_{j,t}$) and with a lag by those variables ordered after it. Similarly, innovations to the variable ordered second affect all variables ordered after it contemporaneously but not the first ordered variable - which it affects only with a lag.

While the ordering of variables for $X_{j,t}$ in Equation 3.14 is therefore important it can be determined quite easily by examining the realisations of these variables. Expected output growth, output disagreement and output uncertainty are all ordered before actual output growth (as in Leduc and Liu (2016), Bachmann et al. (2013) and Girardi and Reuter (2017) who all utilise survey data to proxy uncertainty) as these variables are determined from firm responses made at the beginning of period t before output growth is realised. Thus an expected output growth, output disagreement or output uncertainty innovation will contemporaneously affect actual output growth while only being affected by output growth innovations with a lag. While expected output growth, output disagreement and output uncertainty are all determined at the beginning of time t, output uncertainty is ordered first as firms form their expectations while they are uncertain. In other words, firms form their expectations in an environment of already existing uncertainty (be that high or low). Similarly, output disagreement is ordered before expected output growth (but after output uncertainty). Assuming firms receive news mixing local and economy-wide information then according to signal extraction, firms split this single piece of news into the expectation of local and expectation of economy-wide according to the relative variability of the parts - implying the realisation of variability (or output disagreement) prior to expectations. Therefore, $X_{j,t} = (\mu^2_{j,t}, \sigma_{A,j,t}, {}_ty^e_{A,j,t}, y_{j,t})'$, with an ordering determined solely by the realisations of the variables.

While actual output growth ($y_{j,t}$) in $X_{j,t}$ is constructed in genuine differences[29], expected output growth is not as it is the difference between expected output (in levels) and last periods actual output (in levels)[30]. Accordingly, there exists a cointegrating relationship between expected and actual outcomes with cointegrating vector (1, -1). While shocks to

[29] $y_{j,t} = ln(Y_{j,t}) - ln(Y_{j,t-1})$ where $Y_{j,t}$ and $Y_{j,t-1}$ are actual output (in levels) for industrial sector j in periods t and $t-1$ respectively.

[30] ${}_ty^e_{A,j,t} = ln(Y^e_{j,t}) - ln(Y_{j,t-1})$ where $Y^e_{j,t}$ is expected output (in levels) for industrial sector j in period t.

the system have only transitory effects on expected and actual output growth (as well as output uncertainty and output disagreement), they have a permanent (and same-sized) effect on expected and actual output (in levels). Therefore, the system presented in Equation 3.14 is estimated using a CVAR.

3.6.1 The Effects of One Standard Deviation Shocks

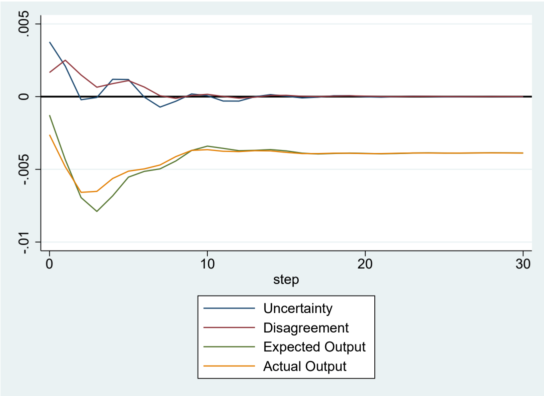
The Augmented Dickey-Fuller test confirms each of the variables in $X_{j,t}$ are I(0). The CVAR is estimated over the period 2002Q2 to 2019Q4, 2007Q4 to 2019Q4 and 2005Q4 to 2019Q4 for the manufacturing and mining, service and distributive trades sectors respectively. Lag length for the CVAR is 3, 2 and 2 for the manufacturing and mining, service and distributive trades sectors (respectively). Post a one standard deviation output uncertainty shock (Figure 3.14a to Figure 3.14c), output disagreement in all three industrial sectors initially increases before gradually returning to its initial level. Both expected and actual output decrease permanently to a lower long-run level value circa 0.2% to 0.6% below their respective initial values - with the impact of an output uncertainty shock being greatest in the distributive trades sector and least in the service sector. Thus, in the long-run the impact of a one standard deviation output uncertainty shock is similar across the three industrial sectors. The effects of a one standard deviation output disagreement shock (Figure 3.15a to Figure 3.15c) are similar - both expected and actual output decrease to permanently lower long-run values.

Post a one standard deviation expected output shock (Figure 3.16a to Figure 3.16c), output uncertainty in the long-run returns to its pre-shock levels - with only the manufacturing and mining sector witnessing a substantial response while the service sector barely registers a response. Similarly, output disagreement returns to its initial level in the long-run - although it follows a different time path in each industrial sector. Actual output increases to a permanently higher long-run value which is circa 1.2% higher than its pre-shock value in the manufacturing and mining and service sectors and circa 2.6% higher in the distributive trades sector. Both the service and distributive trades sector witness a relatively prolonged build-up to this long-run value, while the manufacturing and mining sector exhibits a hump-like shaped response - the impact effect is around 0.5% higher, peaks at 1.4% and then declines to the permanently higher value of 1.2%. In each sector, both expected and actual output converge to the same long-run value. However, convergence is slow and non-monotonic - in contrast to full-information rational expectations[31].

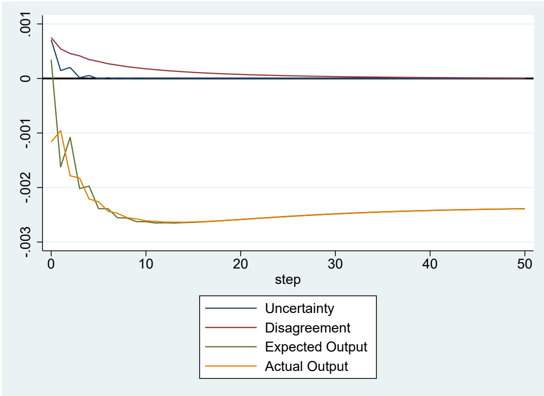
Post a one standard deviation actual output shock (Figure 3.17a to Figure 3.17c), output

[31] Where the response of actual output would mirror the expected output response after one quarter.

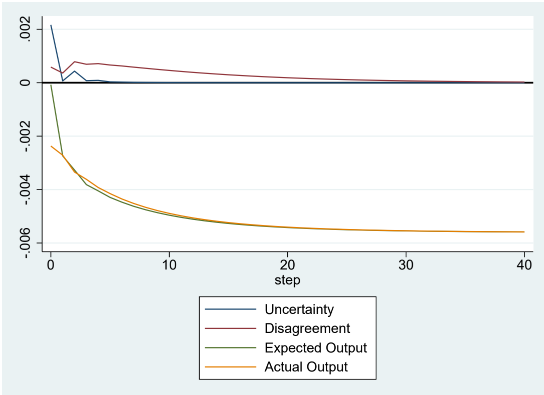
Figure 3.14: Response to One Standard Deviation Output Uncertainty Shock



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms

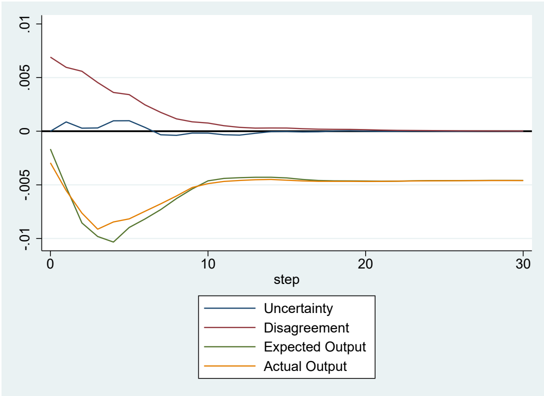


(c) Distributive Trades Sector Firms

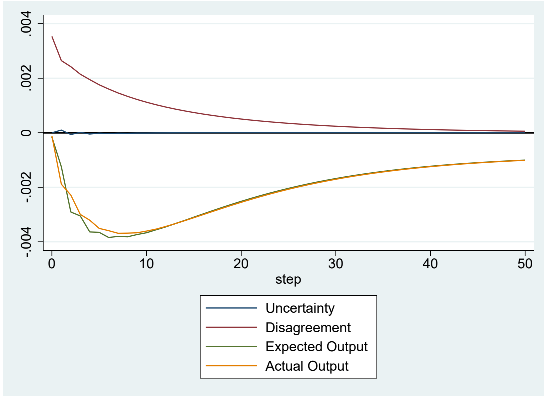
Note: Figure 3.14 depicts the impulse response of a one standard deviation output uncertainty shock to output uncertainty, output disagreement, expected and actual output. For each industrial sector j output uncertainty (defined by the ARCH(q) estimate of the quantitative expectation error) at the beginning of period t is $\mu^2_{j,t} = \zeta_{j,0}+\zeta_{j,1}\varepsilon^2_{j,t-1}+...+\zeta_{j,q}\varepsilon^2_{j,t-q}$, output disagreement (defined by the meta-model adjusted cross-section dispersion of firm survey responses) at the beginning of period t is $\sigma_{A,j,t} = \sqrt{(\alpha^2_{meta,j,t})_t U^e_{j,t} + (\beta^2_{meta,j,t})_t D^e_{j,t} - ((\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t})^2}$ and expected output growth (defined by the meta-model adjusted balance statistic) at the beginning of period t is ${}_t y^e_{A,j,t} = (\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t}$ where $\zeta_{j,1}, ..., \zeta_{j,q}$ are the ARCH parameters and $\varepsilon^2_{j,t-1}, ..., \varepsilon^2_{j,t-q}$ are the squared residuals from a regression of $\epsilon\epsilon_{j,t} = {}_t y^e_{A,j,t} - y_{j,t}$ on it's intercept with $\varepsilon_{j,t}\ N(0, \sigma^2_{j,t})$ and $y_{j,t}$ is actual output growth; Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroskedasticity selects lag length 4, 1 and 1 for the manufacturing and mining, service and distributive trades sectors (respectively); ${}_t U^e_{j,t}$ and ${}_t D^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively); $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Order of variables in the Cointegrating Vector Autoregression (CVAR) for each industrial sector j is output uncertainty, output disagreement, expected output growth and actual output growth. The CVAR is estimated over the period 2002Q2 - 2019Q4, 2007Q4 - 2019Q4 and 2005Q4 - 2019Q4 for the manufacturing and mining, service and distributive trades sectors respectively. Lag length for the CVAR is 3, 2 and 2 for the manufacturing and mining, service and distributive trades sectors (respectively). Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

uncertainty in the long-run returns to its pre-shock levels. However, only in the manufacturing and mining sector do actual output shocks account for appreciable movements

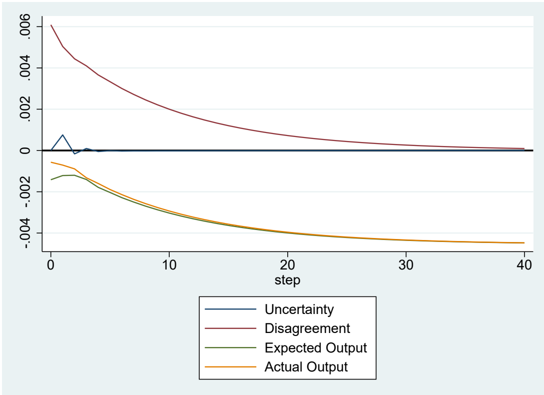
Figure 3.15: Response to One Standard Deviation Output Disagreement Shock



(a) Manufacturing and Mining Firms



(b) Service Firms

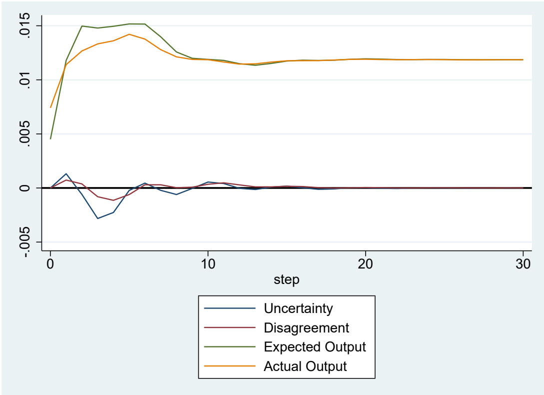


(c) Distributive Trades Firms

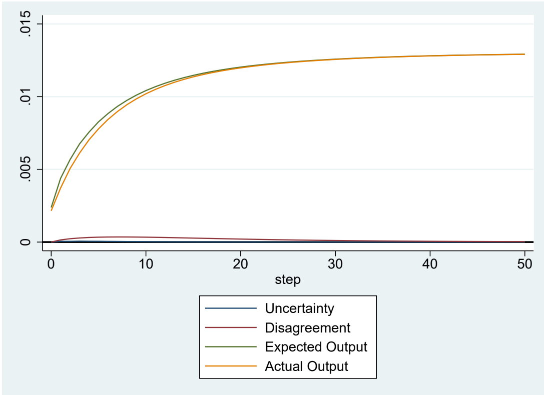
Note: Figure 3.15 depicts the impulse response of a one standard deviation output disagreement shock to output uncertainty, output disagreement, expected and actual output. For each industrial sector j output uncertainty (defined by the ARCH(q) estimate of the quantitative expectation error) at the beginning of period t is $\mu^2_{j,t} = \zeta_{j,0}+\zeta_{j,1}\varepsilon^2_{j,t-1}+...+\zeta_{j,q}\varepsilon^2_{j,t-q}$, output disagreement (defined by the meta-model adjusted cross-section dispersion of firm survey responses) at the beginning of period t is $\sigma_{A,j,t} = \sqrt{(\alpha^2_{meta,j,t})_t U^e_{j,t} + (\beta^2_{meta,j,t})_t D^e_{j,t} - ((\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t})^2}$ and expected output growth (defined by the meta-model adjusted balance statistic) at the beginning of period t is ${}_t y^e_{A,j,t} = (\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t}$ where $\zeta_{j,1}, ..., \zeta_{j,q}$ are the ARCH parameters and $\varepsilon^2_{j,t-1}, ..., \varepsilon^2_{j,t-q}$ are the squared residuals from a regression of $\epsilon\epsilon_{j,t} = {}_t y^e_{A,j,t} - y_{j,t}$ on it's intercept with $\varepsilon_{j,t}\ N(0, \sigma^2_{j,t})$ and $y_{j,t}$ is actual output growth; Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroskedasticity selects lag length 4, 1 and 1 for the manufacturing and mining, service and distributive trades sectors (respectively); ${}_t U^e_{j,t}$ and ${}_t D^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively); $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Order of variables in the Cointegrating Vector Autoregression (CVAR) for each industrial sector j is output uncertainty, output disagreement, expected output growth and actual output growth. The CVAR is estimated over the period 2002Q2 - 2019Q4, 2007Q4 - 2019Q4 and 2005Q4 - 2019Q4 for the manufacturing and mining, service and distributive trades sectors respectively. Lag length for the CVAR is 3, 2 and 2 for the manufacturing and mining, service and distributive trades sectors (respectively). Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

in output uncertainty in the short-run. Output disagreement follows a similar (but more pronounced) time path in the manufacturing and mining and service sectors but the opposite path in the distributive trades sectors. In the long-run expected output increases to

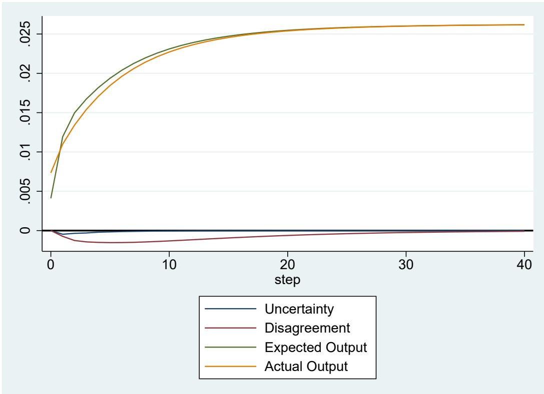
Figure 3.16: Response to One Standard Deviation Expected Output Shock



(a) Manufacturing and Mining Firms



(b) Service Firms

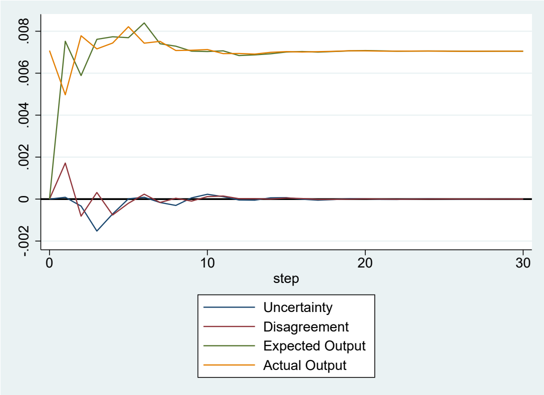


(c) Distributive Trades Firms

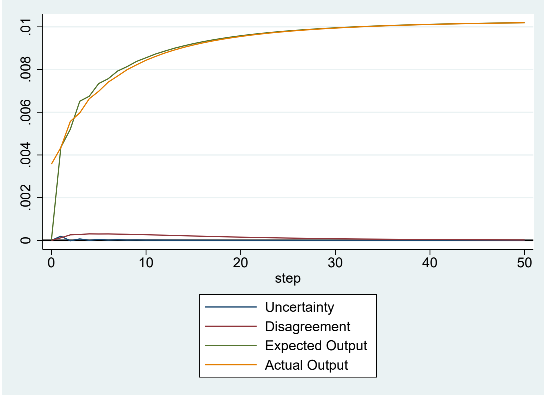
Note: Figure 3.16 depicts the impulse response of a one standard deviation expected output shock to output uncertainty, output disagreement, expected and actual output. For each industrial sector j output uncertainty (defined by the ARCH(q) estimate of the quantitative expectation error) at the beginning of period t is $\mu^2_{j,t} = \zeta_{j,0}+\zeta_{j,1}\varepsilon^2_{j,t-1}+...+\zeta_{j,q}\varepsilon^2_{j,t-q}$, output disagreement (defined by the meta-model adjusted cross-section dispersion of firm survey responses) at the beginning of period t is $\sigma_{A,j,t} = \sqrt{(\alpha^2_{meta,j,t})_tU^e_{j,t} + (\beta^2_{meta,j,t})_tD^e_{j,t} - ((\alpha_{meta,j,t})_tU^e_{j,t} - (\beta_{meta,j,t})_tD^e_{j,t})^2}$ and expected output growth (defined by the meta-model adjusted balance statistic) at the beginning of period t is ${}_ty^e_{A,j,t} = (\alpha_{meta,j,t})_tU^e_{j,t} - (\beta_{meta,j,t})_tD^e_{j,t}$ where $\zeta_{j,1},...,\zeta_{j,q}$ are the ARCH parameters and $\varepsilon^2_{j,t-1},...,\varepsilon^2_{j,t-q}$ are the squared residuals from a regression of $\epsilon\epsilon_{j,t} = {}_ty^e_{A,j,t} - y_{j,t}$ on it's intercept with $\varepsilon_{j,t}\ N(0,\sigma^2_{j,t})$ and $y_{j,t}$ is actual output growth; Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroskedasticity selects lag length 4, 1 and 1 for the manufacturing and mining, service and distributive trades sectors (respectively); ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively); $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Order of variables in the Cointegrating Vector Autoregression (CVAR) for each industrial sector j is output uncertainty, output disagreement, expected output growth and actual output growth. The CVAR is estimated over the period 2002Q2 - 2019Q4, 2007Q4 - 2019Q4 and 2005Q4 - 2019Q4 for the manufacturing and mining, service and distributive trades sectors respectively. Lag length for the CVAR is 3, 2 and 2 for the manufacturing and mining, service and distributive trades sectors (respectively). Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

a permanently higher values circa 0.7%, 1% and 1.8% higher than their pre-shock values in the manufacturing and mining, service and distributive trades sectors (respectively).

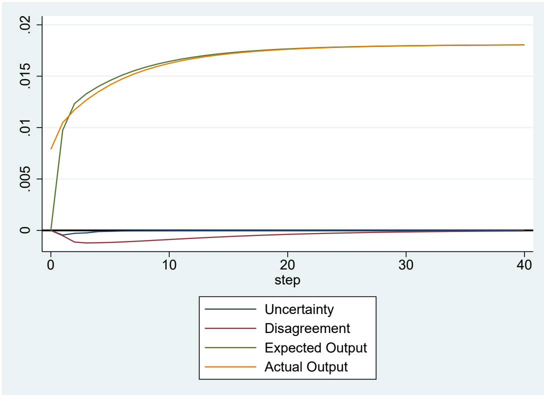
Figure 3.17: Response to One Standard Deviation Actual Output Shock



(a) Manufacturing and Mining Firms



(b) Service Firms



(c) Distributive Trades Firms

Note: Figure 3.17 depicts the impulse response of a one standard deviation actual output shock to output uncertainty, output disagreement, expected and actual output. For each industrial sector j output uncertainty (defined by the ARCH(q) estimate of the quantitative expectation error) at the beginning of period t is $\mu^2_{j,t} = \zeta_{j,0} + \zeta_{j,1}\varepsilon^2_{j,t-1} + ... + \zeta_{j,q}\varepsilon^2_{j,t-q}$, output disagreement (defined by the meta-model adjusted cross-section dispersion of firm survey responses) at the beginning of period t is $\sigma_{A,j,t} = \sqrt{(\alpha^2_{meta,j,t})_t U^e_{j,t} + (\beta^2_{meta,j,t})_t D^e_{j,t} - ((\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t})^2}$ and expected output growth (defined by the meta-model adjusted balance statistic) at the beginning of period t is ${}_t y^e_{A,j,t} = (\alpha_{meta,j,t})_t U^e_{j,t} - (\beta_{meta,j,t})_t D^e_{j,t}$ where $\zeta_{j,1}, ..., \zeta_{j,q}$ are the ARCH parameters and $\varepsilon^2_{j,t-1}, ..., \varepsilon^2_{j,t-q}$ are the squared residuals from a regression of $\epsilon\epsilon_{j,t} = {}_t y^e_{A,j,t} - y_{j,t}$ on it's intercept with $\varepsilon_{j,t}\ N(0, \sigma^2_{j,t})$ and $y_{j,t}$ is actual output growth; Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroskedasticity selects lag length 4, 1 and 1 for the manufacturing and mining, service and distributive trades sectors (respectively); ${}_t U^e_{j,t}$ and ${}_t D^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively); $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Order of variables in the Cointegrating Vector Autoregression (CVAR) for each industrial sector j is output uncertainty, output disagreement, expected output growth and actual output growth. The CVAR is estimated over the period 2002Q2 - 2019Q4, 2007Q4 - 2019Q4 and 2005Q4 - 2019Q4 for the manufacturing and mining, service and distributive trades sectors respectively. Lag length for the CVAR is 3, 2 and 2 for the manufacturing and mining, service and distributive trades sectors (respectively). Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

3.6.2 The Effects of Actually Observed Output Uncertainty Shocks in the UK Economy

Figure 3.18a to Figure 3.18c depict the actual output series for each industrial sector along with two corresponding Beveridge-Nelson trend output series - one depicting the steady-state level of output, the other depicting what the steady-state level of output would have been in the absence of output uncertainty or output disagreement shocks post-2007Q4. Assuming no further shocks occur, the Beveridge-Nelson trends show the output level that will be achieved (for all time points) when all current and past shocks have played out[32]. Thus, the Beveridge-Nelson trend is interpreted as the steady-state output level and reflects the size of the shocks actually observed in the data as well as the infinite horizon effects captured by the impulse response functions.

In the manufacturing and mining sector (Figure 3.18a) output decreases circa 2.5% below steady-state during the GFC, but broadly tracks the trend from 2012/2013[33]. In turn, this trend is below the steady-state that would have been observed if there were no shocks to output uncertainty or output disagreement post-2007Q4 throughout the period. Thus shocks to output uncertainty and output disagreement caused trend output to be circa 2.5% to 4.5% lower than it would have been in the absence of shocks through 2008 to 2012, and circa 1% to 2% lower at the end of the sample. Comparably large effects for output uncertainty and output disagreement are observed in the service and the distributive trades sectors (in Figure 3.18b and Figure 3.18c, respectively). However, the timing of the largest effects (during 2011/12 and 2014/15) are later than observed in the manufacturing and mining sector, coinciding more with the timing of the sovereign debt crisis and the UK's discussions on whether to leave the EU.

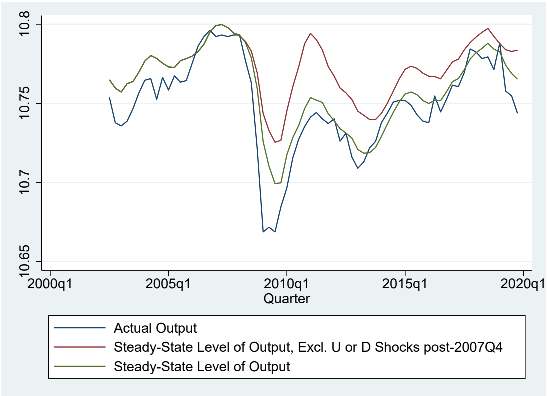
3.7 Conclusion

This study has shown that surveys of firms' expectations provide reliable measures and direct insights on the processes underlying expectation formation and the uncertainty surrounding the process. Omitting these measures from empirical work on output dynamics not only wastes an important source of information but also leads to potentially

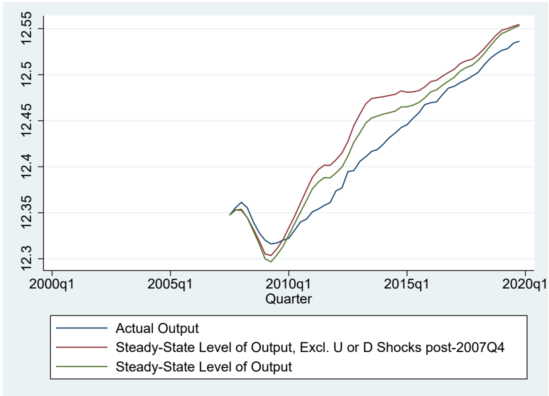
[32]The estimated model provides measures of the actual shocks experienced and their accumulated effect which drives the change in the Beveridge-Nelson trend. The level of the Beveridge-Nelson trend is obtained assuming actual output was at steady state in 2007Q4, arbitrarily chosen at a point just prior to the GFC. For exposition purposes, the plotted Beveridge-Nelson trend is the average value over the previous four quarters.

[33]Note that while actual output fell more than Beveridge-Nelson trend, the latter dropped by circa 7% from peak to trough in the GFC. This provides an explanation regarding why the downward pressure on prices, exerted by a negative gap, was not as large as expected by some contemporary commentators considering the actual output drop alone.

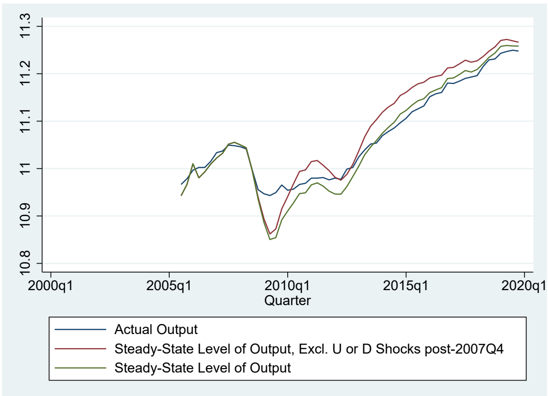
Figure 3.18: The Effects of Observed Output Uncertainty Shocks in the UK using the Beveridge-Nelson Decomposition



(a) Manufacturing and Mining Firms



(b) Service Firms



(c) Distributive Trades Firms

Note: Figure 3.18 depicts the actual output series for each industrial sector along with two corresponding Beveridge-Nelson trend output series - one depicting the steady-state level of output, the other depicting what the steady-state level of output would have been in the absence of output uncertainty or output disagreement shocks post-2007Q4. The level of the Beveridge-Nelson trend is obtained assuming actual output was at steady state in 2007q4, arbitrarily chosen at a point just prior to the GFC. For expositional purposes, the plotted Beveridge-Nelson trend is the average value over the previous 4 quarters.

serious misinterpretation of results - such as including overstatements of the uncertainty surrounding shocks and of the persistent effect or finding a spurious (or over-stated) causal relationship from uncertainty to output growth. One potential reservation in the use of surveys is that many surveys provide only qualitative responses, however the new and novel meta-modelling quantification approach provides a relatively straightforward means of translating these qualitative survey responses into a quantitative series taking into account the changing nature of the relationship between survey responses and outcomes. The expectations and uncertainty series that are derived can then be employed in a relatively straightforward CVAR model that captures the interplay between these series and actual outcomes. Based on the data produced by the CBI for the UK, this study shows these interactions are complex and out-of-line with those suggested by simple models embodying rational expectations - instead requiring more nuanced explanations of firms' use of information and of cognitive limitations and other psychological and social factors in decision-making. There is also a role for output uncertainty and output disagreement shocks in influencing business cycle dynamics - with these having relatively substantial effects of up to 4% in different sectors during GFC and sovereign debt crisis and during the UK's discussions over Brexit.

Chapter 4

Investment and Capacity Utilisation in a Putty-Clay Framework

4.1 Introduction

In the past decade both the Great Financial Crisis (GFC) and the 2016 referendum on membership of the European Union have directly led to sustained periods of low investment for the UK economy[1]. For example, while the ratio of investment to total expenditure was (on average) 13.5% in 2007 it was still only 10.9% in 2012. This is below a G7 average of 14.6%. Furthermore, by 2013Q2 gross fixed capital formation spending was around 25% below its pre-GFC peak (2007Q3). Similarly, since the 2016 referendum business investment has remained weak - contributing to a widening gap between the UK and other G7 countries. Weak firm-level investment has been postulated as a driver of the UK productivity puzzle (the failure of productivity to return to its pre-GFC trend). Thus, understanding the reasons behind this weak firm-level investment is important. However, do existing empirical models provide an adequate explanation for the low levels of post-GFC investment?

In traditional models of investment the adjustment of capital by the firm is driven by a basic relationship between the equilibrium level of capital (K^*) in relation to desired output (Y) - namely, $K^* = \alpha Y$ with parameter α. Firm-level investment (i.e. the adjustment to capital by the firm) is determined by a flexible accelerator model such as $I_t = \sum_{s=1}^{S} \beta_s K^*_{t-s}$. There are no adjustment costs in this simple framework with dynamics reflecting the lag between changes to output and changes to capital stock. By adding prices and a constant returns Cobb-Douglas technology to this basic framework, Jorgenson

[1]This chapter is based on Lee et al. (2022).

(1963) created the neoclassical theory of investment. The corresponding optimisation problem (involving a perfectly competitive firm with no adjustment costs and myopic expectations) yields the standard static first-order condition $K = \alpha\frac{Y}{\phi^K}$, where ϕ^K is the cost of capital. Brainard and Tobin (1968) and Tobin (1969) proposed that investment should be positively related to the ratio of the value of the firm to the cost of purchasing the firm's capital (Tobin's Q). Abel (1979) and Hayashi (1982) derived the marginal q theory of investment by linking the neoclassical model with convex adjustment costs (where q is the marginal value of an installed unit of capital). While this provided a satisfactory theory of long run investment (since the log of the static first-order condition $K = \alpha\frac{Y}{\phi^K}$ can produce an equilibrium condition of the form $k - y = \eta\phi^K$, disregarding constants and the unit elasticity constraint) it has little to say about dynamics.

Furthermore, are firms free to adjust their capital and labour stock in response to a demand shock? If yes, then capital is described as putty-putty. Both pre- and post-installation of capital, there is perfect substitution between capital and labour (as in the Cobb-Douglas production function). If no, then capital is described as putty-clay (originally introduced by Johansen (1959)). Pre-installation capital is putty, but post-installation capital is combined with labour in a fixed proportion (i.e. technology is now Leontief with no perfect substitution between capital and labour). Putty-putty technology assumes capital post-installation can be used for any task or purpose (i.e. capital has many uses and is easily reoriented and adjusted in the face of demand shocks). With putty-putty technology all resources are used fully - there is no idle capital when a firm is producing its output as any unused capital would be reoriented to reduce variable costs. In reality, capital is task specific post-installation and cannot easily or quickly be reoriented or adjusted to complete tasks other than that for which it was designed. That is capital is task-specific post-installation - as in putty-clay technology. In a putty-clay environment, variation in post-installation production (when technology is Leontief) is achieved by greater or lesser capital or labour intensity. In the short-run, it is more realistic that capital and labour are fixed and firms make use of inventories, management of the order book and greater or lesser capacity utilisation to meet demand. Thus, assuming putty-putty technology has strong (unrealistic) implications.

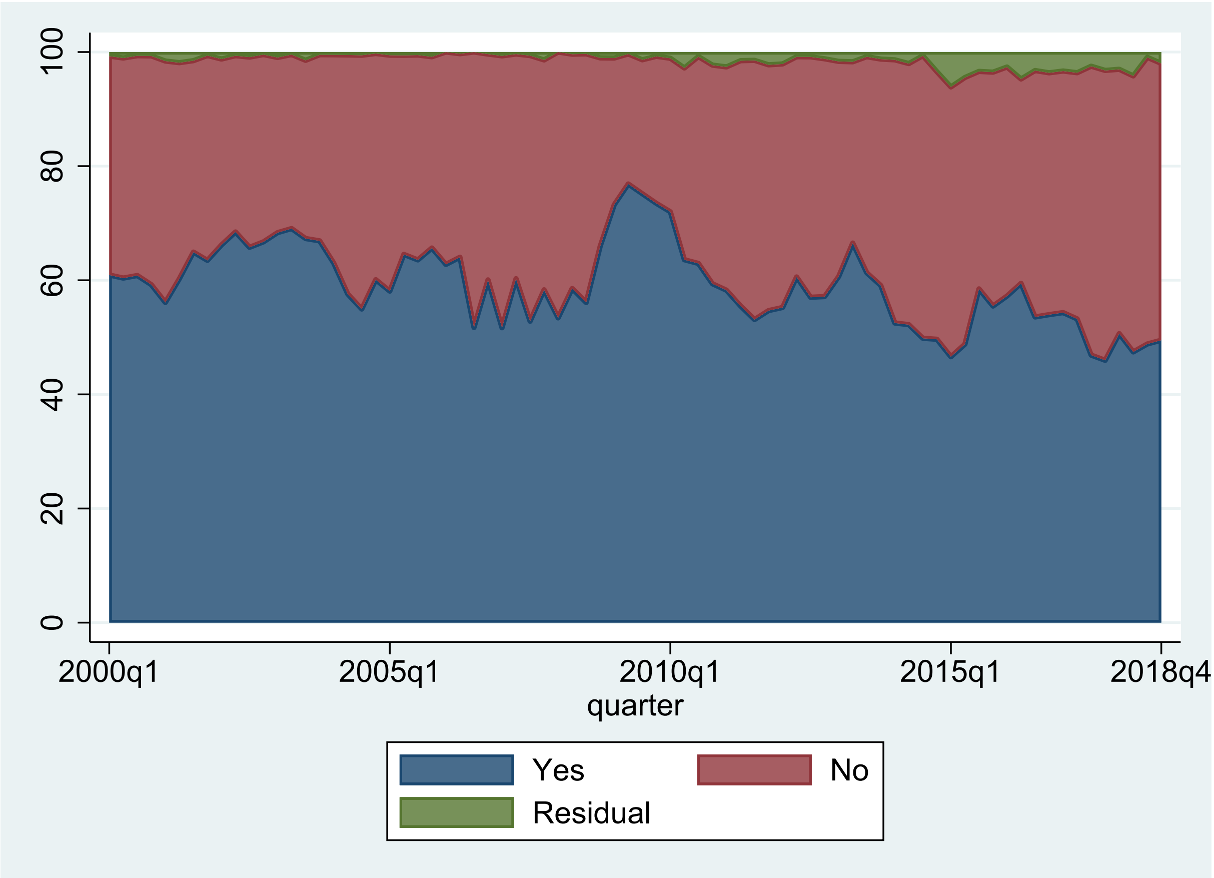
Assuming at any point in time the stocks of capital and labour are fixed, the firm must choose the corresponding degree of utilisation. Abel and Eberly (1994, 1996), Doms and Dunne (1994), Caballero, Engel and Haltiwanger (1995) and Cooper, Haltiwanger and Power (1999) have shown non-convexities and irreversibility in investment have a profound effect on investment decisions. In addition, there is considerable evidence (at the plant-level) that adjustment of investment to driving variables is a non-linear relationship - explaining why there are investment bursts followed by periods of inaction (Cooper and Haltiwanger, 2005). However, these models have given little attention to capacity utilisation. One reason is that capacity utilisation is not readily obtained from accounting data (as capital and labour inputs are). Nevertheless, consideration of capacity utilisation is important for putty-clay models - since it is the key adjustment margin in the short run.

While a direct measure of capacity utilisation is not available from company accounts data, it is readily available from firm-level survey data for the UK. The Confederation of British Industry (CBI) Industrial Trends Survey (ITS) asks participating firms if they are working below a satisfactory full rate of operation and their current rate of capacity utilisation. The latter constitutes a direct measure of capacity utilisation, while the former provides evidence of putty-clay technology. Figure 4.1 graphs the proportion of firms selecting "yes" and "no" to question 4 of the ITS where respondents are asked "Is your present level of output below capacity (i.e. are you working below a satisfactory full rate of operation)?"[2]. It demonstrates a majority of firms operate below full capacity (aside from 2017Q3, 2017Q4 and 2018Q3). In fact, on average only 39.28% of firms fully utilise their resources over the period 2000Q1 to 2018Q4. Thus over the sample period a majority of firms (on average 59.19%) have idle capital while producing output. Even excluding the extreme changes in survey responses around the GFC the conclusion remains unchanged - between 2000Q1 and 2007Q4 61.69% of firms (on average) and between 2011Q1 and 2018Q4 54.18% of firms (on average) have spare excess capacity. The presence of this continuous excess capacity over the course of the sample indicates that capital is not putty-putty, but rather putty-clay. Therefore, it is more reasonable to assume the existence of putty-clay technology. In contrast to (say) the accelerator model of investment where factors are perfectly adjustable, capital and labour are now fixed with firms unable to adjust these factors in the face of demand. Therefore, firms adjust their rate of capacity utilisation in response to demand - and is thus a firm decision variable in the firm maximisation problem.

By using a unique matched dataset (combining a direct measure of capacity utilisation taken from firm-level surveys with capital and labour inputs taken from company accounts data) this chapter uses putty-clay models to introduce a relationship between investment and capacity utilisation. Namely, in the short-run when factors of production are fixed firms instead adjust their rate of capacity utilisation to meet demand. As documented in Figure 4.1 firms have spare excess capacity, which can be utilised in the short-run to meet demand while in the longer term investment and new hiring can take place. Ignoring the role of capacity utilisation as a short-term buffer overestimates the adjustment of capital back to its long-run equilibrium. For example, in the standard accelerator model of investment this would manifest in a capital error correction term being too large in absolute

[2] See Section 4.3 (and in particular Section 4.3.1 for information on the direct measure of capacity utilisation) for further details on the data contained in the ITS.

Figure 4.1: Is your present level of output below capacity i.e. are you working below a satisfactory full rate of operation?



Source: The Confederation of British Industry (CBI) Industrial Trends Survey (ITS) question 4 “Is your present level of output below capacity (ie. are you working below a satisfactory full rate of operation)?”.

terms (i.e. implying capital returns to its long-run value of sales quicker than it actually does). However, as documented existing literature has largely ignored the role of capacity utilisation in estimating firm-level investment equations. This chapter documents the important role of capacity utilisation as a short-term buffer by updating the Abel (1981) framework to derive a putty-clay accelerator model of investment. The key distinction between this putty-clay accelerator model and the classic accelerator version is the former includes a capacity error correction term. Thus, this new putty-clay accelerator model of investment directly incorporates the role of capacity utilisation as a short-run buffer. Not only is the inclusion of the capacity error correction term itself significant (reflecting the short-run behaviour of firms) but it should also reduce (in absolute value) the coefficient on the capital error correction term (reflecting the slower estimated adjustment of capital to equilibrium). Both of these empirical facts are confirmed in the empirical section of this chapter where the putty-putty and putty-clay accelerator models of investment are estimated using system GMM. A key conclusion of this chapter is that omitting capacity utilisation from an accelerator model of investment overestimates the adjustment speed of capital as it ignores the ability of firms to adjust their utilisation of capital, which could provide an explanation for sluggish investment in the UK economy post-GFC. The structure of the chapter is as follows: Section 4.2 of the chapter derives this theoretical model extending the framework of Abel (1981). It is then implemented using the matched CBI and Bureau van Dijk FAME dataset - with data sources summarised in Section 4.3 and results presented in Section 4.4. Section 4.5 concludes.

4.2 Theory

This section derives firm-level investment equations, first assuming putty-putty technology in Section 4.2.1 (where the capital and labour stock are free to adjust) and second using putty-clay technology in Section 4.2.2 (where firms adjust their rate of capacity utilisation in response to demand, given their factors of production are fixed).

4.2.1 A Baseline Model of Investment

Consider a simple firm maximisation problem, where the firm maximises the present value of its flow of funds as in Equation 4.1.

$$max \sum_{t=0}^{\infty} \beta^t (p_{j,t} A_{j,t} K_{j,t}^{\alpha} L_{j,t}^{1-\alpha} - \hat{p}_{j,t} I_{j,t}^{K}) \tag{4.1}$$

subject to the constraint $K_{j,t+1} = I_{j,t}^{K} + (1-\delta)K_{j,t}$ where for firm j in period t $p_{j,t}$ is the price of output, $A_{j,t}$ is the state of technology, $K_{j,t}$ is capital stock, $L_{j,t}$ is labour stock, $\hat{p}_{j,t}$ is the price of capital, $I_{j,t}^{K}$ is investment in capital goods and δ is the rate of capital depreciation. The firm production function is a standard Cobb-Douglas, $Y_{j,t} = A_{j,t} K_{j,t}^{\alpha} L_{j,t}^{1-\alpha}$, where the capital and labour stock are not fixed, and firms can freely adjust these factors of production in response to demand. Setting the Lagrangian and solving yields Equation 4.2:

$$K_{j,t} = \alpha \frac{Y_{j,t}}{\phi_{j,t}^{K}} \tag{4.2}$$

where $Y_{j,t}$ is output and $\phi_{j,t}^{K}$ is the user cost of capital. Taking logs of Equation 4.2 yields Equation 4.3, showing that in the long-run capital is proportional to output (or sales) and the user cost of capital[3].

$$k_{j,t} = y_{j,t} + \varphi_{j,t} \tag{4.3}$$

Following Mairesse et al. (1999) the dynamic adjustment of capital and sales for firm j each period can be captured by constructing an autoregressive distributed lag (ARDL)

[3] $k_{j,t} = log(K_{j,t})$, $y_t = log(Y_{j,t})$ and $\varphi_{j,t} = log(\alpha) - log(\phi_{j,t}^{K})$.

model of order one for capital and sales as per Equation 4.4[4].

$$k_{j,t} = \xi_0 + \xi_1 k_{j,t-1} + \xi_2 y_{j,t} + \xi_3 y_{j,t-1} + \eta_{j,t} \tag{4.4}$$

where $\eta_{j,t} = \varphi_{j,t} + \psi_j + \psi_t$ with ψ_j and ψ_t as the firm and year fixed effects (respectively).

Equation 4.3 is nested within Equation 4.4 as its long-run solution. Specifically, as $t \to \infty$ and given no shocks then $y_{j,t} \to y_j^*$ where y_j^* is the steady-state long-run equilibrium value of $y_{j,t}$. Then given $\eta_{i,j,t} = 0$ $k_{j,t} \to k_j^*$ where k_j^* is the steady-state long-run equilibrium value of $k_{j,t}$ as defined in Equation 4.5:

$$\begin{aligned} k_j^* &= \xi_0 + \xi_1 k_j^* + \xi_2 y_j^* + \xi_3 y_j^* \\ &= \frac{\xi_0}{1-\xi_1} + \frac{\xi_2 + \xi_3}{1-\xi_1} y_j^* \end{aligned} \tag{4.5}$$

Combining Equation 4.3 with Equation 4.5 yields:

$$\frac{\xi_0}{1-\xi_1} = \varphi_t \tag{4.6}$$

and

$$\frac{\xi_2 + \xi_3}{1-\xi_1} = 1 \tag{4.7}$$

Substituting Equation 4.6 and Equation 4.7 into Equation 4.4 and taking the first difference of $k_{j,t}$ yields the resulting error correction form of Equation 4.4.

$$\Delta k_{j,t} = \xi_0 + \xi_2 \Delta y_{j,t} + (\xi_1 - 1)(k_{j,t-1} - y_{j,t-1}) + \eta_{j,t} \tag{4.8}$$

where for each firm j in period t $\Delta k_{j,t} = k_{j,t} - k_{j,t-1}$ is the investment rate, $\Delta y_{j,t} = y_{j,t} - y_{j,t-1}$ is the growth in sales, $(\xi_1 - 1)$ is the capital error correction coefficient and $(k_{j,t-1} - y_{j,t-1})$ is the degree of the breakdown in the long-run relationship between $\kappa_{j,t}$ and $y_{j,t}$. Equation 4.8 is the accelerator model of investment with error correction. Short-run dynamics, measuring the immediate impact of $\Delta y_{j,t}$ on $\Delta k_{j,t}$, are captured by ξ_2. Long-run dynamics, measuring the correction of the disequilibrium each period, are encapsulated in $(\xi_1 - 1)$. A priori it is expected that $-1 < (\xi_1 - 1) < 0$, indicating that future investment increases when capital falls below its desirable long-run level. The closer $(\xi_1 - 1)$ is to 0 (-1) the slower (quicker) the disequilibrium correcting process (if $(\xi_1 - 1)$ is 0 (-1) then no (full) error-correcting behaviour occurs). In the short-run, $k_{j,t}$ can wander from its long-run equilibrium path - but in the long-run $(\xi_1 - 1)$ will pull it back. In other words, an adjustment mechanism exists where previous period equilibrium deviations (measured by $(k_{j,t-1} - y_{j,t-1})$) lead to an adjustment in $k_{j,t}$.

[4]While Mairesse et al. (1999) uses an ARDL of order two, using an ARDL of order one yields an investment equation specification as in Bloom et al. (2007) and Kang et al. (2014).

Bond et al. (2003), Bloom et al. (2007) and Kang et al. (2014) have each taken an accelerator model of investment and augmented it with additional control variables. The lagged investment captures the dynamic adjustment of the investment rate - and is included in investment equation specifications such as Ghosal and Loungani (2000), Bond et al. (2003), Bassetto and Kalatzis (2011) and Kang et al. (2014). Both Bloom et al. (2007) and Kang et al. (2014) include sales growth squared to capture the potential non-linear effect of sales growth on investment. A statistically significant positive sales growth squared coefficient implies a convex relationship between investment and demand shocks. Ghosal and Loungani (2000), Bond et al. (2003), Bloom et al. (2007), Bassetto and Kalatzis (2011) and Kang et al. (2014) include cash-flow (and its lag) in investment specifications as it can reflect finance constraints, future profitability opportunities or measurement errors. Investment constraints (for example, uncertainty or finance) are found in Ghosal and Loungani (2000), Temple et al. (2001), Bloom et al. (2007), Driver et al. (2008) and Kang et al. (2014). Although von Kalckreuth (2006) does not estimate an investment equation, this study did show (using data from the CBI) that financially constrained firms take longer to close capacity gaps (where a capacity gap indicates a divergence between actual and desired capital stock). Thus Equation 4.8 can be rewritten as Equation 4.9.

$$\begin{aligned}\Delta k_{j,t} = \xi_0 + \zeta_1 \Delta k_{j,t-1} + \zeta_2 \frac{c_{j,t}}{K_{j,t-1}} + \zeta_3 \frac{c_{j,t-1}}{K_{j,t-2}} + \zeta_4 (\Delta y_{j,t})^2 \\ + \xi_2 \Delta y_{j,t} + (\xi_1 - 1)(k_{j,t-1} - y_{j,t-1}) + \theta_1 \Gamma_{j,t} + \eta_{j,t}\end{aligned} \tag{4.9}$$

where for each firm j in period t $\Delta k_{j,t-1}$ is the lag investment rate, $c_{j,t}$ is the log of cash-flow which is normalised by last periods capital stock ($K_{j,t-1}$) and $\Gamma_{j,t}$ is a factor (or set of factors) which pose a constraint on firm-level investment. Examples of possible investment constraints include uncertainty (firms may implement a wait-and-see policy during periods of heightened uncertainty, thus limiting investment), inadequate finance (if firms are unable to obtain sufficient funds for investment this constrains their ability to invest) or poor proposed return on investment (if a potential investment project is not predicted to be sufficiently profitable firms may divert resources elsewhere). The effect of investment constraints on the investment behaviour of firms is captured by θ_1. Equation 4.9 is similar to specifications found in Mairesse et al. (1999), Bond et al. (2003), Bloom et al. (2007) and Kang et al. (2014).

4.2.2 A Model of Investment Including Capacity Utilisation

This subsection outlines a model of investment (based on Abel (1981)) where firms adjust their rate of capacity utilisation in response to demand, as they are no longer free to adjust their fixed stocks of capital and labour. Dynamic behaviour comes through the accumulation of the capital and labour stock.

4.2.2.1 Defining the Production Problem

As in Equation 4.1, firms use capital and labour to produce output - but now both factors of production are quasi-fixed. That is, at the beginning of period t (before the state of nature is revealed) both capital and labour stocks are fixed and determined by decisions made in period $t-1$. Thus, once the state of nature is revealed in period t firms are unable to adjust their capital or labour stocks. Therefore, in order to respond to demand firms adjust how intensively they use capital and labour in their production process. In other words, the firm decision is to determine its rate of capacity utilisation (and through this the rate of effective capital and effective labour)[5]. In a variation of the production function proposed by Abel (1981), Equation 4.10 includes the rate of utilisation in the production function of firm j by interacting it with the labour stock:

$$Y_{j,t} = A_{j,t} K_{j,t}^{\alpha} (\Omega_{j,t} L_{j,t})^{1-\alpha} \tag{4.10}$$

where for firm j in period t $Y_{j,t}$ is output, $A_{j,t}$ is the level of technology, $K_{j,t}$ is the capital stock, $\Omega_{j,t}$ is the rate of capacity utilisation, $L_{j,t}$ is the labour stock and $\Omega_{j,t} L_{j,t}$ is effective labour (also called labour services)[6]. To be clear, the firm production decision at any time t (once labour and capital are installed) is to choose a value for $\Omega_{j,t}$. Interacting the rate of capacity utilisation with the labour stock reflects that increased capacity utilisation operates through increased use of the labour stock (for example through overtime, zero-hour contracts or agency work). That is, in order to use machines more intensively this requires increased use of the labour stock[7].

Adjusting the rate of capacity utilisation is not costless as it involves increased use of the labour stock. Simply put, if a firm wishes to increase its rate of capacity utilisation it needs to increase the use of its labour stock. As employees are working more intensively (for example through overtime) this increases the wage bill for the firm. Accordingly, the total wage per employee $W_{j,t}$ is a product of the hourly wage rate and capacity utilisation (reflecting the intensive use of the labour stock). The hourly wage rate is a (weakly) convex function of capacity utilisation such that total wage per employee is defined by

[5]See for example Abel (1981), Gilchrist and Williams (2005), Auernheimer and Trupkin (2014) and Bachmann (2015) for papers which have followed a similar setup.

[6]Abel (1981) assumes there exists a labour utilisation rate and a capital utilisation rate, such that capital utilisation is a function of labour utilisation. In contrast, $\Omega_{j,t}$ in Equation 4.10 is a capacity utilisation rate encompassing the utilisation rates of the labour and capital stock in one measure.

[7]To be clear, in order to meet demand in the short-run firms increase their rate of capacity utilisation. This requires intensifying the use of already installed capital (via increased use of the labour stock).

Equation 4.11 (Abel, 1981):

$$W_{j,t} = \left(\frac{w_{j,t}}{2}\Omega_{j,t}\right)(\Omega_{j,t}) \tag{4.11}$$

where $w_{j,t}$ is the nominal scale wage rate and $\left(\frac{1}{2}\Omega_{j,t}\right)$ is the premium rate per worker. As in Abel (1981) it is assumed that the only cost to increasing capacity utilisation is through increased use of the labour stock[8].

As well as deciding on the rate of capacity utilisation, investment in the capital stock and labour stock are decision variables for the firm in each period t. Adjusting these stocks involves a (convex) cost of adjustment, given by Equation 4.12 and Equation 4.13 (for the capital stock and labour stock, respectively):

$$X^K(I^K_{j,t}, K_{j,t}) = \frac{\gamma}{2}\left(\frac{I^K_{j,t}}{K_{j,t}}\right)^2 K_{j,t} \tag{4.12}$$

$$X^L(I^L_{j,t}, \Omega_{j,t}L_{j,t}) = \frac{\varepsilon}{2}\left(\frac{I^L_{j,t}}{\Omega_{j,t}L_{j,t}}\right)^2 \Omega_{j,t}L_{j,t} \tag{4.13}$$

where γ and ε are the coefficients measuring the marginal cost of capital and labour adjustment (respectively). Since Equation 4.12 and Equation 4.13 exhibit constant returns to scale, they can be respecified in terms of an investment-capital or investment-labour ratio as in Equation 4.14 and Equation 4.15 (respectively).

$$x^K\left(\frac{I^K_{j,t}}{K_{j,t}}\right) = X^K\left(\frac{I^K_{j,t}}{K_{j,t}}, 1\right) = \frac{\gamma}{2}\left(\frac{I^K_{j,t}}{K_{j,t}}\right)^2 \tag{4.14}$$

$$x^L\left(\frac{I^L_{j,t}}{\Omega_{j,t}L_{j,t}}\right) = X^L\left(\frac{I^L_{j,t}}{\Omega_{j,t}L_{j,t}}, 1\right) = \frac{\varepsilon}{2}\left(\frac{I^L_{j,t}}{\Omega_{j,t}L_{j,t}}\right)^2 \tag{4.15}$$

where (without loss of generality) $x^K(0) = 0$, $x^{K'}(0) = 0$, $x^{K'}(a) = \gamma(a) > 0$ if $a > 0$ and $\mathrm{x}^{K''}(a) = \gamma$. Note that both Equation 4.13 and Equation 4.15 are constructed in terms of effective labour - reflecting the role of capacity utilisation in the use of labour stock to produce output.

[8]The wage bill of the firm (i.e. the variable cost of production) is proportional to the labour stock and not directly related to the capital stock. Accordingly, the marginal cost of utilisation is an increasing function of the labour stock and is unrelated to the capital stock (Abel, 1981). This also echoes Lucas (1970) where utilisation is defined as the fraction of hours capital works over a given period. Thus, the rate of capacity utilisation depends on wages. The assumption that the only cost to increased capacity utilisation is the increase in wages is also found in Gilchrist and Williams (2000, 2005).

4.2.2.2 The Firm Maximisation Problem

The firm optimisation problem is to maximise the present value of its flow of funds with decision variables capacity utilisation, investment in capital stock ($I^K_{j,t}$) and investment in labour stock ($I^L_{j,t}$) - see Equation 4.16:

$$\begin{aligned}&\max_{\Omega, I^K, I^L} \sum_{t=0}^{\infty} \beta^t \left(p_{j,t} A_{j,t} K^{\alpha}_{j,t} (\Omega_{j,t} L_{j,t})^{1-\alpha} - \left(\frac{w_{j,t}}{2} \Omega_{j,t} \right) (\Omega_{j,t}) L_{j,t} \right. \\ &\left. - \frac{\gamma}{2} \left(\frac{I^K_{j,t}}{K_{j,t}} \right)^2 I^K_{j,t} - \frac{\varepsilon}{2} \left(\frac{I^L_{j,t}}{\Omega_{j,t} L_{j,t}} \right)^2 I^L_{j,t} \right)\end{aligned} \tag{4.16}$$

subject to $K_{j,t+1} = I^K_{j,t} + (1-\delta) K_{j,t}$ and $\Omega_{j,t+1} L_{j,t+1} = I^L_{j,t} + (1-\mu)\Omega_{j,t} L_{j,t}$. The first term in the maximisation problem is the product of the price of output $p_{j,t}$ with output (defined by the production function given in Equation 4.10). The second term is the product of the total wage per employee (defined in Equation 4.11 with the labour stock). The third term and fourth terms are the convex cost of capital and labour adjustment, given by Equation 4.14 and Equation 4.15 (respectively). The maximisation constraints are the standard equations of motion where δ and μ are the depreciation of the capital and effective labour stock (respectively). Equation 4.16 is similar to the firm maximisation problem considered by Abel (1981) and it enhances the simple maximisation problem of Equation 4.1 by including capacity utilisation (thus allowing for idle factors of production) and adjustment costs[9].

The firm maximisation problem is solved by constructing and maximising, with respect to the decision variables, the Lagrangian in Equation 4.17:

$$\begin{aligned}\mathfrak{L}_{j,t} = &\sum_{t=0}^{\infty} \beta^t \left(p_{j,t} A_{j,t} K^{\alpha}_{j,t} (\Omega_{j,t} L_{j,t})^{1-\alpha} - \left(\frac{w_{j,t}}{2} \Omega_{j,t} \right) (\Omega_{j,t}) L_{j,t} \right. \\ &- \frac{\gamma}{2} \left(\frac{I^K_{j,t}}{K_{j,t}} \right)^2 I^K_{j,t} - \frac{\varepsilon}{2} \left(\frac{I^L_{j,t}}{\Omega_{j,t} L_{j,t}} \right)^2 I^L_{j,t} \\ &+ p^K_{j,t} (I^K_{j,t} + (1-\delta) K_{j,t} - K_{j,t+1}) \\ &\left. + p^L_{j,t} (I^L_{j,t} + (1-\mu) \Omega_{j,t} L_{j,t} - \Omega_{j,t+1} L_{j,t+1}) \right)\end{aligned} \tag{4.17}$$

where $p^K_{j,t}$ and $p^L_{j,t}$ are the shadow price of capital and labour (respectively)[10].

[9] The difference between the Abel (1981) specification and Equation 4.16 derives from the production function in Equation 4.10 (and thus Equation 4.15) being written in terms of effective labour (i.e. the interaction term between the rate of capacity utilisation and the labour stock).

[10] Also called the demand price of capital investment and labour investment, respectively.

The short-run equilibrium is given by Equation 4.18, Equation 4.19 and Equation 4.20.

$$\Omega_{j,t} = (1-\alpha)\frac{A_{j,t}}{\tilde{w}_{j,t}}\kappa_{j,t}^{\alpha} + \frac{1}{w_{j,t}}\left(\varepsilon\left(\frac{I_{j,t}^{L}}{\Omega_{j,t}L_{j,t}}\right)^{3} - p_{j,t}^{L}\mu\right) \tag{4.18}$$

$$\left(\frac{I^K}{K}\right)_{j,t} = \left(\frac{1}{3}\frac{2}{\gamma}p_{j,t}^{K}\right)^{\frac{1}{2}} \tag{4.19}$$

$$\left(\frac{I^L}{\Omega L}\right)_{j,t} = \left(\frac{1}{3}\frac{2}{\varepsilon}p_{j,t}^{L}\right)^{\frac{1}{2}} \tag{4.20}$$

where $\kappa_{j,t} = \frac{K_{j,t}}{\Omega_{j,t}L_{j,t}}$ is capital per effective worker, $p_{j,t}^{L}\mu$ is the required rate of return and $\tilde{w}_{j,t} = \frac{w_{j,t}}{p_{j,t}}$ is the real scale wage. Similar to Abel (1981) the optimal rate of capacity utilisation is an increasing (decreasing) function of the capital-effective labour ratio (real wage rate). By enhancing the firm-maximisation problem with effective labour, the optimal rate of capacity utilisation is also an increasing (decreasing) function of the investment-effective labour ratio (the required rate of return and total scale wage cost). Both the optimal investment-capital ratio and investment-effective labour ratio are increasing functions of the shadow price of capital and effective labour respectively - as in Abel (1981).

The intertemporal equations are given by Equation 4.21 and Equation 4.22.

$$\Delta p_{j,t}^{K} = (r+\delta)p_{j,t}^{K} - \alpha p_{j,t}\frac{Y_{j,t}}{K_{j,t}} - \gamma\left(\frac{I^K}{K}\right)_{j,t}^{3} \tag{4.21}$$

$$\Delta p_{j,t}^{L} = (r+\mu)p_{j,t}^{L} - (1-\alpha)p_{j,t}A_{j,t}\kappa_{t}^{\alpha} + \frac{w_t}{2}\Omega_{j,t} - \varepsilon\left(\frac{I^L}{\Omega L}\right)_{j,t}^{3} \tag{4.22}$$

where $\Delta p_{j,t}^{K}$ and $\Delta p_{j,t}^{L}$ are the capital gain per unit of capital and effective labour (respectively). Rearranging Equation 4.21 shows that the required rate of return per unit of installed capital ($(r+\delta)p_{j,t}^{K}$) equals the realised return; which is the sum of the marginal revenue product of one unit of capital ($\alpha p_{j,t}\frac{Y_{j,t}}{K_{j,t}}$), the saving in installation cost resulting from the decrease in $\frac{I^K}{K}$ due to one extra unit of capital ($\gamma\left(\frac{I^K}{K}\right)_{j,t}^{3}$) and the capital gain per unit of capital ($\Delta p_{j,t}^{K}$). Note that $(r+\delta)p_{j,t}^{K}$ is the user cost of capital, thus for ease of notation (and comparison with the putty-putty framework) let $\phi_{j,t}^{K} = (r+\delta)p_{j,t}^{K}$. Rearranging Equation 4.22 shows that the required rate of return per unit of effective labour ($(r+\mu)p_{j,t}^{L}$) equals the realised return; which is the sum of the net marginal revenue product of one unit of effective labour ($(1-\alpha)p_{j,t}A_{j,t}\kappa_{t}^{\alpha} - \frac{w_t}{2}\Omega_{j,t}$), the saving in installation cost resulting from the decrease in $\frac{I^L}{\Omega L}$ due to one extra unit of effective labour ($\varepsilon\left(\frac{I^L}{\Omega L}\right)_{j,t}^{3}$) and the capital gain per unit of effective labour ($\Delta p_{j,t}^{L}$). Note that Equation 4.22 is analogous to Equation 4.21, thus $(r+\mu)p^L_{j,t}$ is the user cost of labour. For ease of notation let $\phi^L_{j,t} = (r+\mu)p^L_{j,t}$. Furthermore, since $\frac{I^L}{L}_{j,t} \approx 0$ it can be dropped from Equation 4.22[11].

4.2.2.3 The Steady State

The steady-state of the system (i.e. the long-run values of capital and capacity utilisation) resulting from Equation 4.16 is provided by Equation 4.23 and Equation 4.24.

$$K^* = \alpha \frac{Y}{\phi^K} \tag{4.23}$$

$$\Omega^* = \frac{\phi^L}{w} \tag{4.24}$$

The solution method for Equation 4.23 and Equation 4.24 involves setting Equation 4.21 and 4.22 to zero and solve for K^* and Ω^*, respectively (see Appendix E.2 for details). Note that Equation 4.23 is the same as Equation 4.2. Thus, in the long-run capital is proportional to output (or sales) and the user cost of capital in a putty-putty and putty-clay framework. In the long-run, capacity is proportional to the user cost of labour[12].

4.2.2.4 The Linearised System Around the Steady State

Following Abel (1981) a system linearised around the steady-states (defined by Equation 4.23 and Equation 4.24) can be derived in terms of $\Delta k_{j,t}$ and $\Delta\Omega_{j,t}$ (using Equation 4.21 and Equation 4.22 - see Appendix E.2). Focusing on the investment in capital goods component of this linearised system yields Equation 4.25 - which provides a description of the adjustment (in investment in capital goods) in the local area around the steady-state:

$$\Delta k_{j,t} = \lambda^k_1 \Delta k_{j,t-1} + \lambda^k_2 (k_{j,t-1} - k^*_{j,t-1}) + \lambda^k_3 (\Omega_{j,t-1} - \Omega^*_{j,t-1}) + \epsilon^k_{j,t} \tag{4.25}$$

where for each firm j in period t $(k_{j,t-1} - k^*_{j,t-1})$ is the investment in capital error correction term (with steady-state defined by Equation 4.23) and $(\Omega_{j,t-1} - \Omega^*_{j,t-1})$ is the capacity utilisation error correction term (with steady-state defined by Equation 4.24). Like $(\xi_1 - 1)$ in Equation 4.8 and Equation 4.9, λ^k_2 is the capital error correction term coefficient which measures the extent to which previous period equilibrium deviations (measured by $(k_{j,t-1} - k^*_{j,t-1})$) lead to an adjustment in $k_{j,t}$. As before, $k_{j,t}$ is free to deviate from its long-run equilibrium path - but will be pulled back by λ^k_2 in the long-run. As with $(\xi_1 - 1)$,

[11] The empirical justification for setting $\frac{I^L}{L}_{j,t} \approx 0$ is in the Appendix E.2. Specifically see Figure E.1 and Figure E.2 which show that $\frac{I^L}{L}_{j,t} \approx 0$ for the sample of firms.

[12] Recall from Section 4.2.2.2 the required rate of return per unit of effective labour equals the realised return, which is the sum of the net marginal revenue product of labour, the installation cost saving due to an extra unit of installed labour and the capital gain. This analogous to Abel (1981).

it is expected that $-1 < \lambda_2^k < 0$ - with the speed of adjustment depending on the closeness to 0 or -1 (as with $(\xi_1 - 1)$). λ_3^k is the capacity error correction term (and is absent from Equation 4.8 or Equation 4.9), which captures the previous periods deviation of capacity from its long-run equilibrium value[13]. In contrast to λ_2^k, it is expected that $\lambda_3^k > 0$ as firms unable to adjust their capital stock (since it is fixed in a putty-clay environment) instead alter their rate of capacity utilisation.

As in Section 4.2.1, with Equation 4.8, Equation 4.25 can be rewritten as Equation 4.26[14].

$$\begin{aligned} \Delta k_{j,t} = \xi_0^k + \lambda_1^k \Delta k_{j,t-1} + \zeta_2^k \frac{c_{j,t}}{K_{j,t-1}} + \zeta_3^k \frac{c_{j,t-1}}{K_{j,t-2}} + \zeta_4^k (\Delta y_{j,t})^2 \\ + \xi_2^k \Delta y_{j,t} + \lambda_2^k (k_{j,t-1} - k_{j,t-1}^*) + \lambda_3^k (\Omega_{j,t-1} - \Omega_{j,t-1}^*) \\ + \theta_1^k \Gamma_{j,t} + \epsilon_{j,t}^k \end{aligned} \tag{4.26}$$

Equation 4.27 is the capacity utilisation component of the linearised system - which provides a description of the adjustment (in the growth of the rate of capacity utilisation) in the local area around the steady-state:

$$\Delta\Omega_{j,t} = \lambda_1^\Omega \Delta\Omega_{j,t-1} + \lambda_2^\Omega (k_{j,t-1} - k_{j,t-1}^*) + \lambda_3^\Omega (\Omega_{j,t-1} - \Omega_{j,t-1}^*) + \epsilon_{j,t}^\Omega \tag{4.27}$$

where for each firm j in period t $(k_{j,t-1} - k_{j,t-1}^*)$ is the investment in capital error correction term (with steady-state defined by Equation 4.23) and $(\Omega_{j,t-1} - \Omega_{j,t-1}^*)$ is the capacity utilisation error correction term (with steady-state defined by Equation 4.24). λ_3^Ω is the capacity error correction term coefficient which measures the extent to which previous period equilibrium deviations (measured by $\Omega_{j,t-1} - \Omega_{j,t-1}^*$) lead to an adjustment in $\Delta\Omega_{j,t}$. Similar to Equation 4.25, $\Delta\Omega_{j,t}$ is free to deviate from its long-run equilibrium path - but will be pulled back by λ_3^Ω in the long-run. As with $(\xi_1 - 1)$ and λ_2^k, it is expected that $-1 < \lambda_3^\Omega < 0$ - with the speed of adjustment depending on the closeness to 0 or -1. Thus, there is a consistent interpretation of $(\xi_1 - 1)$, λ_2^k and λ_3^Ω across Equation 4.9, Equation 4.26 and Equation 4.27 (respectively). λ_2^Ω is the capital error correction term, which captures the previous periods deviation of capital from its long-run equilibrium value. It is expected that λ_2^Ω is statistically insignificant - indicating that capacity utilisation is an

[13]Previous studies, such as Bean (1981), have included capacity utilisation in their investment specifications with the purpose of exploring a potential causal relationship. In contrast, this study includes a capacity error correction term, which represents the breakdown in the relationship between the rate of capacity utilisation and its long-run equilibrium value. This captures the extent to which deviations of the rate of capacity utilisation from its desired long-run equilibrium act as a short-run buffer in response to demand when the stock of capital is fixed. In the putty-clay framework firms are unable to instantaneously adjust their stock of capital, instead intensifying the use of their existing stock. However, this is only as a short-run solution and in the long-run the rate of capacity utilisation returns to its equilibrium value.

[14]That is following authors such as Bond et al. (2003), Bloom et al. (2007) and Kang et al. (2014) include additional control variables to the baseline investment specification such as cash-flow, sales growth (squared) and investment constraints.

exogenous process as it depends only on its own lags and own disequilibrium correction process.

As cash-flow, lag cash-flow, sales growth, sales growth squared and investment constraints are important explanatory variables for investment in capital goods, they should also be included in Equation 4.27 as they could also be important in explaining the growth of capacity utilisation. Thus, Equation 4.27 can be rewritten as Equation 4.28[15].

$$\begin{aligned}\Delta\Omega_{j,t} = {} & \xi_0^{\Omega} + \lambda_1^{\Omega}\Delta\Omega_{j,t-1} + \zeta_2^{\Omega}\frac{c_{j,t}}{K_{j,t-1}} + \zeta_3^{\Omega}\frac{c_{j,t-1}}{K_{j,t-2}} + \zeta_4^{\Omega}(\Delta y_{j,t})^2 \\ & + \xi_2^{\Omega}\Delta y_{j,t} + \lambda_2^{\Omega}(k_{j,t-1} - k_{j,t-1}^{*}) + \lambda_3^{\Omega}(\Omega_{j,t-1} - \Omega_{j,t-1}^{*}) \\ & + \theta_1^{\Omega}\Gamma_{j,t} + \epsilon_{j,t}^{\Omega}\end{aligned} \tag{4.28}$$

Equation 4.9, Equation 4.26 and Equation 4.28 are estimated using the system GMM approach of Arellano and Bover (1995) and Blundell and Bond (1998), which combines a system of equations in first differences and levels where the respective instruments are the lagged level and difference of endogenous variables. Validity of the instruments is tested using the Hansen test of overidentifying restrictions while the Lagrange multiplier tests for serial correlation in the error term. Recall the only difference between Equation 4.9 and Equation 4.26 is the inclusion of the capacity error correction term in the latter. This reflects that Equation 4.9 corresponds to a putty-putty environment (where firms are free to adjust their factors of production) while Equation 4.26 corresponds to a putty-clay environment (where factors of production are fixed post-installation and firms instead adjust their rate of capacity utilisation). Thus, the capital error correction term is expected to be lower in Equation 4.26 (i.e. the putty-clay environment) than Equation 4.9 (i.e. the putty-putty environment) as firms adjust their rate of capacity utilisation as capital is now a fixed factor. Thus, in a putty-clay environment capital takes longer to adjust to its long-run equilibrium value.

4.3 Data

There are two primary data sources for this chapter - the Confederation of British Industry (CBI) Industrial Trends Survey (ITS) and the Bureau van Dijk FAME dataset. The ITS covers the UK manufacturing and mining sector since 1958, with voluntary participation not limited by CBI membership. The ITS is a monthly business tendency survey, supplemented each quarter with a set of additional questions from both the CBI and the Bank of England. Collection for the survey published in month t begins around the final

[15]Following the argument outlined in Section 4.2.1 for Equation 4.8 and to maintain consistency with Equation 4.26.

week of month $t-1$ with publication of results around the final week of month t. For example, the January survey round questionnaire is issued around the last week of December with the concurrent results published around the last week of January. Variables relevant to this study measured by the ITS include capacity utilisation and investment constraints[16]. ITS firm-level data is available from 2000Q1 to 2018Q4 - with a total of 4,496 firms (and 45,204 corresponding survey observations).

The Bureau van Dijk FAME dataset is an annual dataset of company accounts data from firms registered with Companies House dating back to 2000. There are around 12.6 million firms in the FAME dataset of which 5.6 million are active and 7 million are inactive. Of the 5.6 million active firms 3 million have a detailed financial format, 300,000 have a summary financial format and around 2.3 million do not have filed accounts (either they are not required or have not yet filed their first accounts). For each firm the FAME dataset records basic firm details including (among others) firm name (including previous firm names), Company House number, registered office address, SIC07 code, audit details, number of employees, company type, company status and details on directors (current and past). In addition, the FAME dataset includes 63 profit and loss items, 75 balance sheet items, 10 cash-flow items and 29 financial and profitability ratios. It also includes data on credit scores and limits, Gazette data and six years of County Court Judgement history and mortgage data[17]. For quoted firms the FAME dataset includes main exchange and ticker symbol, security and price information, LSE indices, current and annual stock data and valuations, daily, weekly and monthly pricing series and market capitalisation figures and advisors. FAME annual company accounts data is available from 2000 to 2018[18]. Merging the FAME to the CBI dataset yields 2,188 firms with 24,156 corresponding survey observations.

Lee et al. (2020a) provide a comprehensive overview of the ITS (including matching it to the Bureau van Dijk FAME dataset). The remainder of this section is based on this discussion paper - specifically, aspects of the ITS and FAME datasets relating to capacity and investment.

4.3.1 Capacity Data from the Industrial Trends Survey (ITS)

There are two questions related to capacity utilisation in the quarterly ITS. Question 4 asks firms if their present level of output is below capacity - to which they can respond either yes or no. Survey responses to this question are used in constructing Figure 4.1,

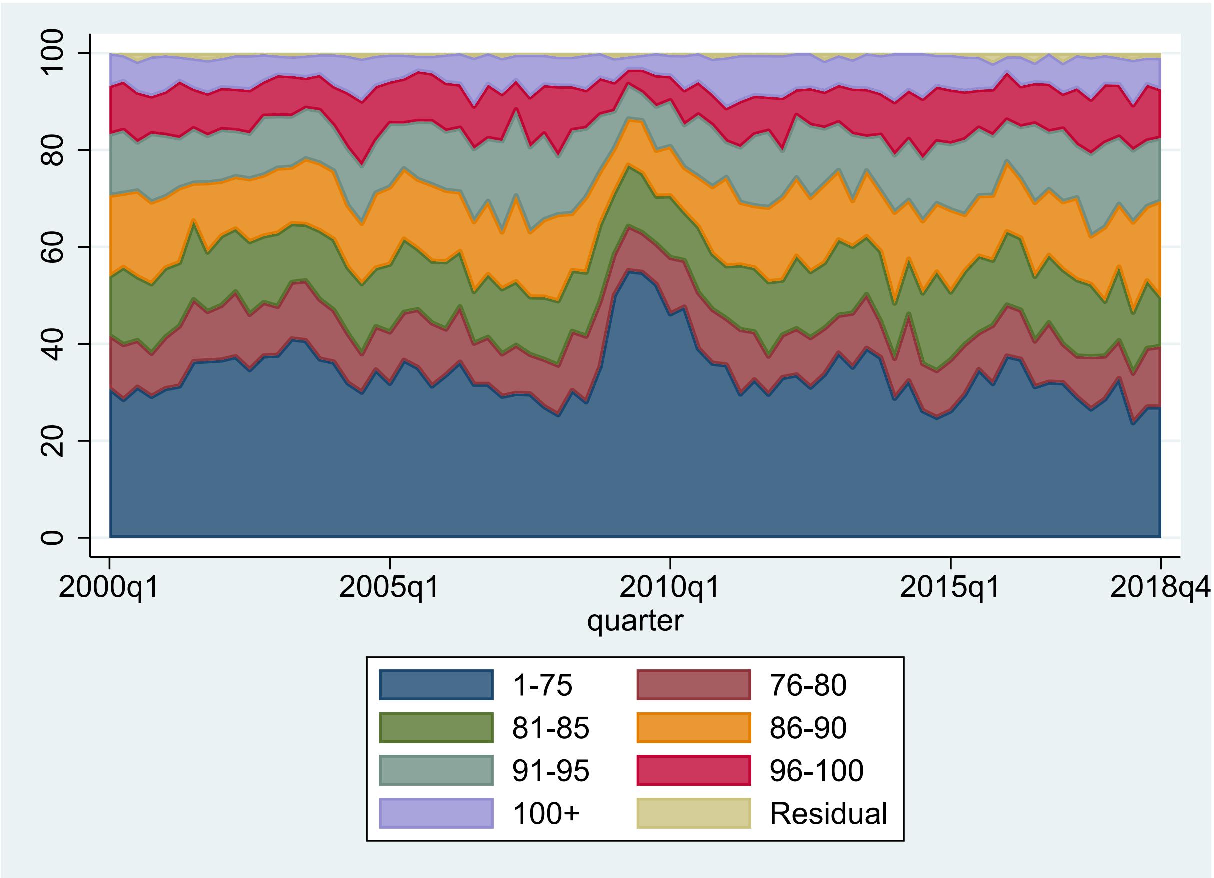
[16]Questions related to capacity utilisation and investment constraints are only included in the ITS once a quarter

[17]Gazette data is official data related to company insolvency and deceased estates data.

[18]This is in contrast to the ITS data which is quarterly - therefore quarterly ITS data is aggregated up to annual data.

which forms the motivational backdrop to this study. A direct firm-level measure of the rate of capacity utilisation is provided by question 4a which asks firms to detail their current rate of operation as a percentage of full capacity. Firms can choose from twenty-one bins of five-increment percentages starting at 1% - 5% and ending at 100+% - results are presented in Figure 4.2 as the proportion of firms selecting each percentage bin each quarter with all firms selecting less than 76% being aggregated into one measure. The time paths depicted in Figure 4.2 indicate that during the financial crisis and Great Recession the proportion of firms operating at less than 76% increases markedly, while the proportion of firms operating at higher rates of capacity decreases.

Figure 4.2: What is your current rate of operation as a percentage of full capacity?



Source: The Confederation of British Industry (CBI) Industrial Trends Survey (ITS) question 4a "What is your current rate of operation as a percentage of full capacity?".

To allow comparison with the annual company accounts data from FAME, an annual measure of capacity utilisation is constructed by taking the yearly mean of firm survey responses to Question 4a.

4.3.2 Investment Constraint Data from the Industrial Trends Survey (ITS)

Question 16c of the ITS asks firms what are the likely factors (either wholly or partly) which could limit investment over the next twelve months; with possible answers "inadequate net return on proposed investment", "shortage of internal finance", "inability to raise external finance", "cost of finance", "uncertainty about demand", "shortage of labour" and "other". Firms rank these factors in order of importance - but are not obliged to rank all factors, ranking only those which are applicable. In addition to this being a broad list of potential investment constraints, the distinct advantage of the CBI dataset is that firms self-identify as being constrained. This direct measure of investment constraints ensure there is no need for recourse to a potentially poor or noisy proxy. By taking the firm-average of survey responses throughout the year firm-level investment constraint dummies ${}_{t-1}poor_{j,t}$, ${}_{t-1}internal_{j,t}$, ${}_{t-1}external_{j,t}$, ${}_{t-1}cost_{j,t}$, ${}_{t-1}uncertainty_{j,t}$, ${}_{t-1}labour_{j,t}$ and ${}_{t-1}other_{j,t}$ are constructed[19]. As the survey question is forward-looking these investment constraint dummies, which refer to investment in period t, are constructed in period $t-1$ (thus the pre-subscript of $t-1$ before each variable). For example, ${}_{t-1}poor_{j,t}$ states (on average) if firm j is constrained by "inadequate net return" in period t based on their survey responses in period $t-1$. Each constraint dummy takes a value of 1 when the firm is constrained, and 0 otherwise. Figure 4.3 depicts the evolution of the investment constraint dummies over the course of the sample.

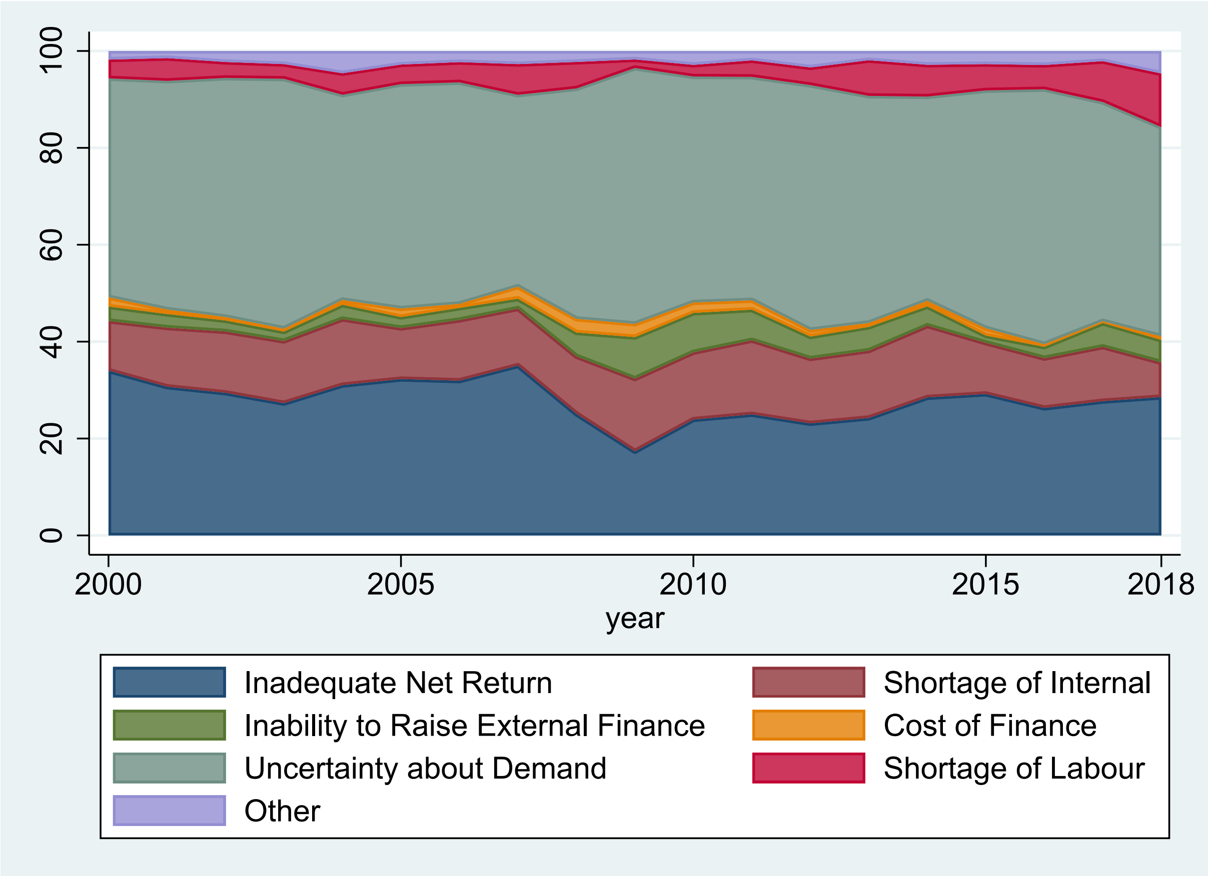
4.3.3 Quantitative FAME Data

Relevant variables to this study contained in the Bureau van Dijk FAME dataset include fixed tangible assets (K), turnover (Y), cash-flow from operating activities (C) and the user cost of labour (ϕ^L). Fixed tangible assets are defined on the firm balance sheet, and are the sum of freehold land, leasehold land, fixtures and fittings, plant and vehicles and other fixed assets. Turnover is taken from the profit and loss account while cash-flow from operating activities is available from the cash-flow statement. The user cost of labour (i.e. the long-run equilibrium value of the rate of capacity utilisation[20]) encompasses all the costs associated with the labour stock - with the wage bill being only one component. Thus, the user cost of labour is the total expenses associated with employees. This can be constructed from items in the profit and loss account. Specifically, the user cost of labour is defined as the sum of wages and salaries, social security costs, pension costs and

[19] The yearly average ranking of each investment constraint is calculated for each firm. A firm is then defined as being constrained by a particular investment constraint if it has a yearly average rank of one or two (chosen to accurately capture the constraining nature of the individual factors).

[20] See Section 4.2.2.3 for details.

Figure 4.3: What factors are likely to limit (wholly or partly) your capital expenditure authorisations over the next twelve months?



Source: The Confederation of British Industry (CBI) Industrial Trends Survey (ITS) question 16c “What factors are likely to limit (wholly or partly) your capital expenditure authorisations over the next twelve months?”. Possible answers are “inadequate net return on proposed investment”, “shortage of internal finance”, “inability to raise external finance”, “cost of finance”, “uncertainty about demand”, “shortage of labour” and “other”.

other staff costs. FAME data is available from 2000 to 2018 and is annual (in contrast to the CBI dataset which is quarterly). All FAME data is winsorised at the first and ninety-ninth percentile to remove the influence of outliers.

Since FAME lacks consistent data on investment in fixed assets for all firms (I^K), fixed tangible assets (K) are used to create the dependent variable (and its lag) in Equation 4.9 and Equation 4.25. The dependent variable for all estimates is $\Delta k_{j,t}$, with Equation

4.29 explaining how this relates to $I^K_{j,t}$.

$$\begin{aligned}
\Delta k_{j,t} &= log\left(\frac{K_{j,t}}{K_{j,t-1}}\right)\\
&= log\left(\frac{K_{j,t}-K_{j,t-1}+K_{j,t-1}}{K_{j,t-1}}\right)\\
&= log\left(\frac{\Delta K_{j,t}}{K_{j,t-1}}+1\right)\\
&\approx \frac{\Delta K_{j,t}}{K_{j,t-1}}\\
&= \frac{I^K_{j,t}}{K_{j,t-1}}-\delta \qquad (4.29)
\end{aligned}$$

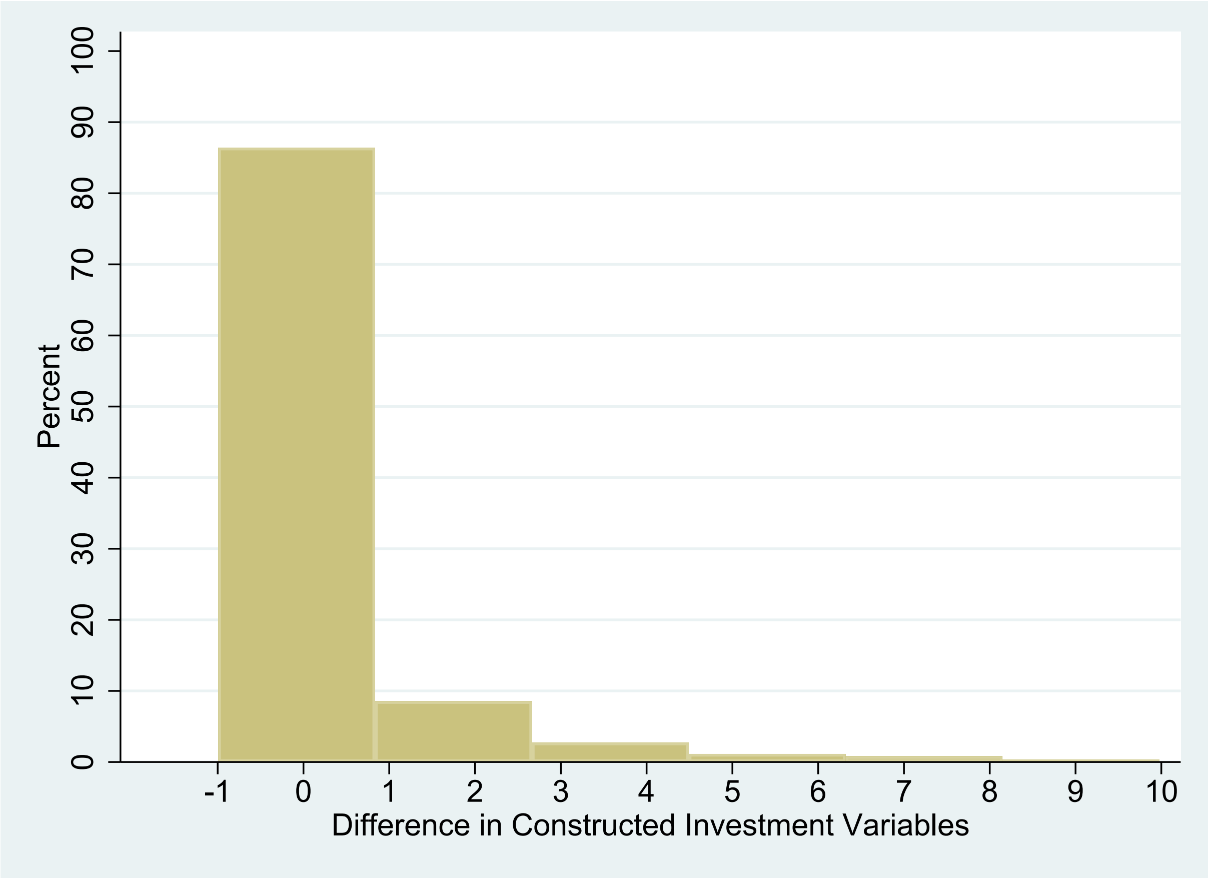
There are 950 firms (with 8,073 observations) in the matched CBI and FAME datasets which have a non-missing value for $\frac{I^K_{j,t}}{K_{j,t-1}}$, while there are 1,946 firms (with 8,791 observations) which have a non-missing value for $\Delta k_{j,t}$. There are 943 firms (with 3,490 observations) which have non-missing values for both $\frac{I^K_{j,t}}{K_{j,t-1}}$ and $\Delta k_{j,t}$. Figure 4.4 plots the histogram of $\frac{I^K_{j,t}}{K_{j,t-1}} - \Delta k_{j,t}$ for 934 of these firms (corresponding to 3,414 observations)[21]. Almost 90% of observations have a difference (in absolute terms) of 1 between $\frac{I^K_{j,t}}{K_{j,t-1}}$ and $\Delta k_{j,t}$. In practice this means that $\frac{I^K_{j,t}}{K_{j,t-1}}$ and $\Delta k_{j,t}$ differ by at most £1,000 for 90% of observations. Furthermore, the percentage of observations decreases substantially as the difference between $\frac{I^K_{j,t}}{K_{j,t-1}}$ and $\Delta k_{j,t}$ increases. Based on the data in Figure 4.4, $\Delta k_{j,t}$ is a valid and reliable alternative to $\frac{I^K_{j,t}}{K_{j,t-1}}$.

4.4 Results

The results of estimating Equation 4.9, Equation 4.25 and Equation 4.27 using system GMM for manufacturing and mining sector data from 2000 to 2018 with the matched CBI and FAME dataset are presented in Table E.1 to Table E.5. Each table presents coefficient estimates (with standard errors in brackets), the number of firms in the estimation sample, the corresponding number of observations and diagnostic tests. For all estimates presented the Arellano-Bond test for autocorrelation rejects second-order serial correlation (and above) in the first-differenced residuals while the Hansen test does not reject the validity of overidentifying restrictions. Following Bloom et al. (2007) the set of instruments for the first-difference equation are the second and third lags of the endogenous variables and the set of instruments for the level equation is the first lag of the endogenous variables. The set of endogenous variables are all the quantitative FAME variables. Table E.1 to Table E.5 follow the same standard layout - column one presents the baseline estimation,

[21] The observations for the remaining 9 firms represent outliers.

Figure 4.4: A Histogram of the Difference between $\frac{I^K_{j,t}}{K_{j,t-1}}$ and $\Delta k_{j,t}$



Note: Figure 4.4 is the histogram the difference between $\frac{I^K_{j,t}}{K_{j,t-1}}$ and $\Delta k_{j,t}$, where the former is provided directly in the FAME dataset and the latter is constructed according to Equation 4.29. There are 934 firms (with 3,414 observations) used for the comparison. All data sourced from Bureau van Dijk FAME dataset. On the x-axis is $\frac{I^K_{j,t}}{K_{j,t-1}} - \Delta k_{j,t}$, while the y-axis is the percentage of observations corresponding to the differences in the x-axis.

columns two to eight individually add investment constraints to the baseline specification and column nine includes all investment constraints with the baseline model.

Table E.1 presents the system GMM estimates of Equation 4.27, where there are 328 firms (and 1,159 observations) in each specification. Only the coefficients on $(\Omega_{j,t-1} - \Omega^*_{j,t-1})$ and $\xi^{\Omega}_2 \Delta y_{j,t}$ are statistically significant (at the 1% level) in any of the specifications. The coefficients on the capacity error correction term, $\hat{\lambda}^{\Omega}_3$, are negative (as expected) indicating that between 70.6% to 71.5% of the deviation between the actual and long-run equilibrium value of capacity is corrected each year. This quick disequilibrium correcting process reflects the firm's ability to instantaneously adjust their usage of existing capital and labour stock as demand dictates. For example, this quick disequilibrium correcting process is in contrast to the much slower capital stock disequilibrium correcting process, presented (later) in Table E.4 and Table E.5 where stocks of capital are fixed in the short-run and cannot be freely adjusted (like the capacity utilisation rate). $\hat{\xi}^{\Omega}_2$ indicates that a 1% increase in sales growth $(\Delta y_{j,t})$ leads to an increase of around 0.5% in $\Delta\Omega_{j,t}$.

Table E.2 presents the system GMM estimates of Equation 4.9, which is the accelerator model of investment with error correction. In the baseline specification (column one) there are 652 firms (with 2,110 observations). Aside from sales growth squared coefficient, each of the variable coefficients are both statistically significant (at least at the 10% significance level) and have the plausibly correct sign. The coefficient on the capital error correction term, $\widehat{\xi_1 - 1}$, is negative (as expected) indicating that around 11.5% of the deviation between actual and long-run equilibrium value of capital is corrected each year. $\hat{\xi_2}$ and $\hat{\zeta_1}$ indicate that a 1% increase in sales growth ($\Delta y_{j,t}$) and the autocorrelation of investment ($\Delta k_{j,t-1}$) leads to an increase of 0.381% and 0.105% (respectively) in $\Delta k_{j,t}$. These results are largely robust to the addition of firm-level investment constraints either individually (in columns two to eight) or altogether (in column nine) - indicating the stability of the baseline model. The inclusion of firm-level investment constraints, measured using firm-level responses to the ITS discussed in Section 4.3.2, reduces the sample size to 444 firms (with 1,556 observations)[22]. Only two investment constraint dummies are statistically significant when added individually - "inadequate net return on proposed investment" (${}_{t-1}poor_{j,t}$, at the 5% significance level) and "uncertainty about demand" (${}_{t-1}uncertainty_{j,t}$, at the 10% significance level). Furthermore, in addition to ${}_{t-1}uncertainty_{j,t}$ leading to a 0.9% reduction in firm-level investment, the positive impact of sales growth on firm-level investment is also marginally reduced compared to the baseline specification (as well as now being statistically significant at the 5% significance level). The statistically significant ${}_{t-1}poor_{j,t}$ reduces the coefficient estimate on the normalised cash-flow variable (compared to the baseline in column one). Firm-level investment is being constrained - both by "inadequate net return on proposed investment" and financial constraints (via the sensitivity of firm-level investment to cash-flow - see Fazzari et al. (1988)). This is also true in column nine where all investment constraints are added simultaneously - note that ${}_{t-1}uncertainty_{j,t}$ is now statistically significant at the 5% significance level.

Table E.3 presents the system GMM estimates of Equation 4.9 augmented with convex adjustment costs ($(\Delta k_{j,t-1})^2$). This reflects that there are costs to adjusting the capital stock each period such as disruption to worker routine, delivery lag of new capital, installation time etc. However, in this model the adjustment cost terms do not seem important. In addition, $\Delta k_{j,t-1}$ is now only statistically significant in the baseline specification (column one) at the 10% significance level. Aside from this, the coefficient estimates in Table E.3 do not substantially deviate from those of Table E.2. Thus, the addition of convex adjustment costs to Equation 4.9 does not enhance the model, and in fact reduces the significance of the persistence of firm-level investment. Either way, in the absence of

[22]This reduction arises due to firm-level investment constraints for year t being measured in year $t-1$ - therefore, firms which appear in the sample beginning in year t only have recorded investment constraint data for year $t+1$ onwards.

capacity utilisation as a decision variable and under the assumption of putty-putty technology both Table E.2 and Table E.3 demonstrate statistically significant capital error correcting behaviour on the part of firms. In each specification $(k_{j,t-1} - y_{j,t-1})$ indicates firms correct around 10% - 10.5% of the imbalance between capital stock and its long-run value (defined by turnover) each year.

Table E.4 presents the system GMM estimates of Equation 4.25 - which augments the classic accelerator model with a capacity error correction term as factors of production are fixed in the short-run in a putty-clay environment[23]. In each specification there are 428 firms (with 1,446 observations)[24]. All coefficient estimates in the baseline (column one) are statistically significant (at least at the 10% significance level). Note this model exhibits greater persistence regarding the firm-level investment rate (compared to Table E.2 and Table E.3) with a 1% increase in $\Delta k_{j,t-1}$ leading to an increase of 0.142% in $\Delta k_{j,t}$. The coefficient on the capital error correction term, $\hat{\lambda}_2^k$, indicates that around 6.4% of the deviation between the actual and long-run equilibrium value of the capital stock is corrected each year. As expected the capital error correction term is negative (as in Table E.2 and Table E.3), but is now only statistically significant at the 10% significance level and the extent to which firms correct the imbalance between capital stock and its long-run equilibrium value each period is now reduced. Instead, there is an increase in the disequilibrium between capacity and its long-run equilibrium value (with $\hat{\lambda}_3^k > 0$, as expected, and statistically significant at the 1% significance level). Thus excluding the capacity error correction term from the firm-level investment equation (as in Equation 4.9) overestimates the extent to which firms respond to disequilibrium between actual and desired investment (while at the same time underestimating the role of capacity utilisation in the dynamic behaviour of firms). In other words, failing to take the capacity error correction into account overestimates the speed of capital adjustment back to its long-run value. The coefficient on the capacity error correction term is positive due to the actions of firms in the short- and long-run. In the short-run (where the capital and labour stock are fixed) firms meet an increase in demand by increasing the use of capital and labour (i.e. increase their rate of capacity utilisation through increased machine hours, overtime of workers etc.). However, this is only a short-run solution as capital wears out more quickly and labour is more expensive at overtime rates. A better solution to persistent

[23]While the sample dataset is too unbalanced to conduct either a panel test of stationarity or cointegration for $\Omega_{j,t-1}$ and $\Omega^*_{j,t-1}$, some insight can be gained from examining the yearly average of these variables. The p-values of the augmented Dickey-Fuller test for Ω_{t-1} and Ω^*_{t-1} are 0.38 and 0.46 (respectively). Thus in both instances the null hypothesis that a unit root exists fails to be rejected. Furthermore, using the Engle-Granger two-step method the null hypothesis of no cointegration between Ω_{t-1} and Ω^*_{t-1} is rejected (at the 5% statistical significance level).

[24]There is no reduction in sample size with the addition of firm-level investment constraints as Equation 4.25 requires a measure of the lagged capacity utilisation rate. Thus, firms which appear in the sample beginning in year t only have recorded lagged capacity utilisation rate data for year $t+1$ onwards - as with investment constraint data.

demands for more capacity is to invest in more machinery to be used by labour at a more sustainable rate. Thus, in the long-run firms invest more (to augment their capital and labour stock) to meet demand in a more sustainable way. There is still an adjustment of capital to its long-run equilibrium value - but it is now slower than in the putty-putty environment. Finally, note these results are largely robust to the addition of firm-level investment constraints, either individually (column two to eight) or altogether (column nine). In particular, neither the coefficient estimates (nor their statistical significance) of the capital and capacity error correction terms substantially change. Of the firm-level investment constraints, only ${}_{t-1}poor_{j,t}$ and ${}_{t-1}uncertainty_{j,t}$ are statistically significant (both in column two and column nine). As before, the statistically significant ${}_{t-1}poor_{j,t}$ reduces the coefficient estimate on the normalised cash-flow variable (compared to the baseline in column one) - reflecting the reduction in future profit opportunities.

Table E.5 presents the system GMM estimates of Equation 4.25 augmented with sales growth ($\Delta y_{j,t}$) and sales growth squared ($\Delta y_{j,t}^2$). Sales growth is added as Table E.2 and Table E.3 show that it is a statistically significant driver of firm-level investment. Sales growth squared is added to capture any potential non-linearity between sales growth and investment. In each column there are 416 firms (corresponding to 1,425 observations). In column one the coefficient estimates on lagged investment, the two error correction terms, the two cash-flow terms and the sales growth term are statistically significant (at least at the 10% significance level) and have the plausibly correct sign. Sales growth has a statistically significant positive impact on firm-level investment (as in Table E.2 and Table E.3), with the persistence of the investment rate being reduced. Moreover, both error correction terms are statistically significant - with the capacity error correction term highly statistically significant while the capital error correction term is only statistically significant at the 10% significance level. In addition, around 6.5% of the deviation between actual and long-run equilibrium values is corrected each year - in line with the coefficient estimates from Table E.4 and a reduction from the coefficient estimates in Table E.2 and Table E.3. These results are robust to the addition of firm-level investment constraints - with ${}_{t-1}poor_{j,t}$ being the only statistically significant investment constraint (either when the investment constraints are added individually, or altogether as in column nine). Thus, the baseline model presented in column one of Table E.4 is robust to the addition of sales growth and a series of investment constraints.

Bond et al. (2003) and Bloom et al. (2007) have previously estimated an accelerator model of investment with error correction (i.e. an equation similar to Equation 4.9) for a set of UK firms over 1978-1989 and 1973-1991 (respectively). The speed of adjustment of capital to its long-run value is slower in both Bond et al. (2003) and Bloom et al. (2007) than either Table E.2 or Table E.3. Specifically, in absolute terms Bond et al. (2003) has a coefficient estimates of 0.071 for the capital error correction term while Bloom et al. (2007) have coefficient estimates ranging from 0.053 to 0.062. Both of these estimates are smaller in absolute terms than the -0.115 to -0.127 in Table E.2 or Table E.3. Both the Bond et al. (2003) and Bloom et al. (2007) capital error correction term coefficients are more in line with estimates from Table E.4 and Table E.5. A key conclusion of this chapter is that respecifying the classic accelerator model to include a capacity error correction term is an important factor in explaining the lower estimated capital error correction coefficient. Yet Bond et al. (2003) and Bloom et al. (2007) do not include a capacity error correction term and achieve a similar adjustment speed for capital[25]. An explanation for this is that over the time period of both studies capacity was close to its long-run value - thus making the capacity disequilibrium term negligible. However, once this disequilibrium term expands ignoring it overestimates the speed of capital adjustment back to its long-run value.

The key implication from comparing Table E.5 with Table E.2 is that the dynamic adjustment of investment in capital stock is slower when capacity utilisation is accounted for. This is visualised in Figure 4.5 which compares the dynamic response of capital from the traditional accelerator model of investment (Table E.2) with an accelerator model which includes capacity utilisation (Table E.5). This is achieved by rewriting Equation 4.26 and Equation 4.28 into the system defined by Equation 4.30.

$$\begin{aligned} \begin{pmatrix} k_{j,t} \\ \Omega_{j,t} \end{pmatrix} &= \begin{pmatrix} \xi_0^k - \lambda_2^k k_{j,t-1}^* \\ \xi_0^\Omega - \lambda_3^\Omega \Omega_{j,t-1}^* \end{pmatrix} + \begin{pmatrix} 1+\lambda_1^k+\lambda_2^k & \lambda_3^k \\ \lambda_2^\Omega & 1+\lambda_1^\Omega+\lambda_3^\Omega \end{pmatrix} \begin{pmatrix} k_{j,t-1} \\ \Omega_{j,t-1} \end{pmatrix} \\ &+ \begin{pmatrix} -\lambda_1^k & 0 \\ 0 & -\lambda_1^\Omega \end{pmatrix} \begin{pmatrix} k_{j,t-2} \\ \Omega_{j,t-2} \end{pmatrix} + \begin{pmatrix} \epsilon_{j,t}^k \\ \epsilon_{j,t}^\Omega \end{pmatrix} \end{aligned} \tag{4.30}$$

Using Equation 4.26 and the system in Equation 4.30, the generalised impulse response function can be generated to examine the dynamic path of $k_{j,t}$ in response to a system-wide shock (i.e. a joint capital and capacity shock). Accordingly, Figure 4.5 depicts the dynamic path of $k_{j,t}$ to a simultaneous 1% $\epsilon_{j,t}^k$ and -0.5348% $\epsilon_{j,t}^\Omega$ shock[26]. The purpose of Figure 4.5 is to compare the dynamic response of capital to a capital shock when capacity utilisation is both unaccounted for (i.e. in a putty-putty environment using estimates from Table E.2) and accounted for (i.e. in a putty-clay environment using estimates from Table E.5)[27]. In both cases the long-run effect of a capital shock on capital is the same but the

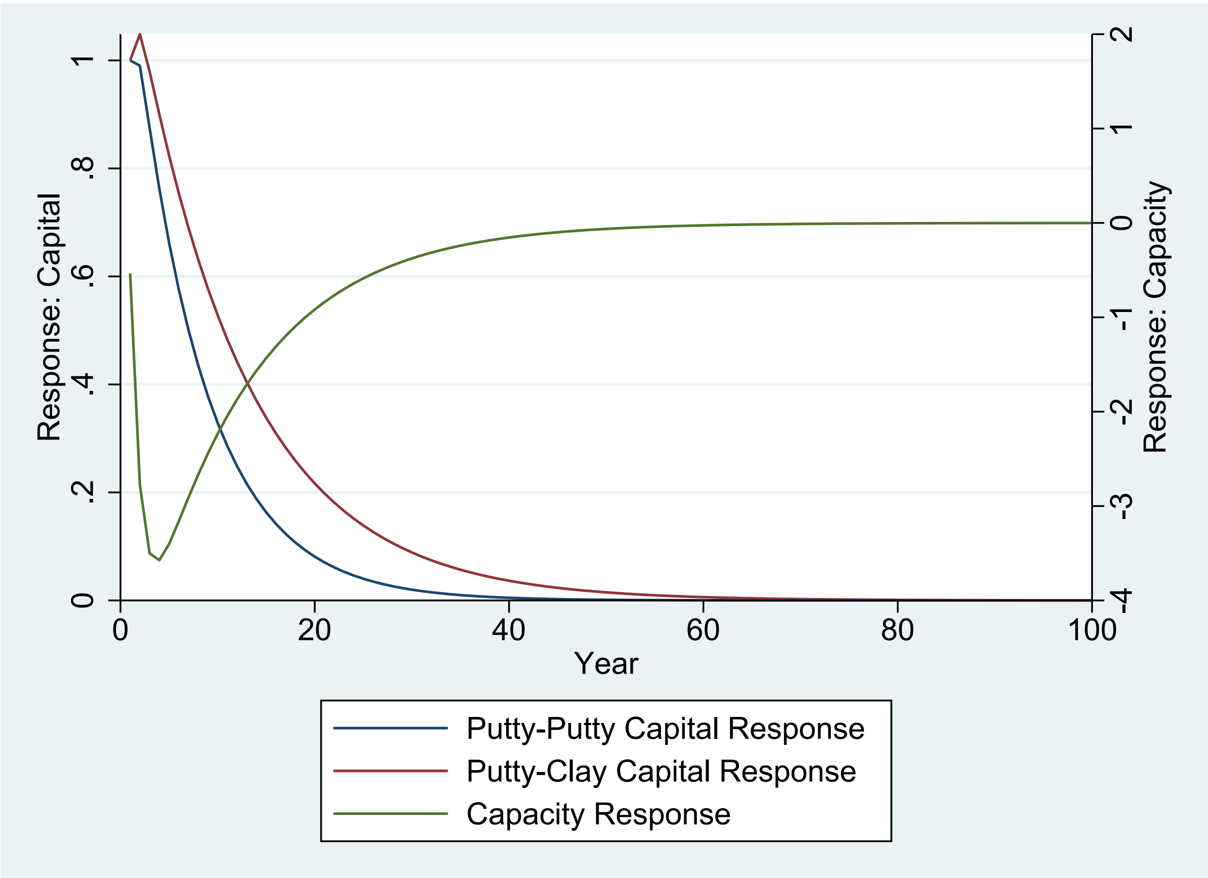
[25]There are two potential reasons for this. First, both sets of authors estimate a model that did not require capacity utilisation as factors of production are adjustable at all times. Second, there is no measure of capacity utilisation available from accounting data such as Bureau van Dijk FAME.

[26]To calculate the generalised impulse response function, the average correlation (across firms) between $\epsilon_{j,t}^k$ and $\epsilon_{j,t}^\Omega$ is calculated. Thus, when $\epsilon_{j,t}^k$ increases by 1% $\epsilon_{j,t}^\Omega$ decreases by 0.5348%.

[27]While the primary focus of this study relates to long-run dynamics of capital, a brief word on the long-run dynamics of capacity are merited. λ_1^Ω, λ_2^Ω and λ_3^Ω from Equation 4.28 are the key coefficients in calculating the response of capacity to a system-wide shock (see Equation 4.30). Thus in constructing the GIRF not only is the coefficient on the capital error correction term important but so too are the coefficients on the capacity lag and capital error correction term.

dynamics are not, as there is a much slower adjustment of capital back to its baseline level when the effect of capacity utilisation is accounted for[28]. This is demonstrated in Table 4.1 which gives the half-life, 75%-life and 90%-life estimates - which are the number of periods it takes the impulse response to the system-wide shock to dissipate by 50%, 75% and 90% (respectively) in the putty-putty and putty-clay environments[29]. For example, in the putty-putty environment 50% adjustment (or the half-life) occurs after 6 periods, but it takes 9 periods for this adjustment to occur in a putty-clay environment. Similarly, 75% of adjustment (the 75%) occurs after 11 periods in a putty-putty environment but 17 periods in a putty-clay environment. While 90% of adjustment (or the 90%-life) occurs after 18 periods when excluding capacity dynamics form the model, it takes 27 periods when capacity dynamics are included. Not only is the speed of adjustment slower in a putty-clay environment, but as the number of periods increases the divergences between the relative speeds of adjustment does too. Thus, the omission of capacity utilisation

Figure 4.5: The Dynamic Response of Capital and Capacity to a System-Wide Shocks



Note: Figure 4.5 depicts the generalised impulse response function of capital and capacity to a system-wide shock. To calculate the generalised impulse response function, the average correlation (across firms) between $\epsilon^{k}_{j,t}$ and $\epsilon^{\Omega}_{j,t}$ is calculated. Thus, when $\epsilon^{k}_{j,t}$ increases by 1% $\epsilon^{\Omega}_{j,t}$ decreases by 0.5348%. The system GMM from Table E.2 and Table E.5 are used to calculate the impulse response functions.

[28]The dynamic path of $k_{j,t}$ to a 1% $\epsilon^{k}_{j,t}$ (i.e. artificially turning off the capacity shock) yields the same results as Figure 4.5.

[29]These are computed directly from the impulse response function.

Table 4.1: The Number of Periods Required for the Impulse Response to the System-Wide Shock to Dissipate by 50%, 75% and 90%.

	Putty-Putty	Putty-Clay
Half-life	6	9
75%-life	11	17
90%-life	18	27

Note: Half-life is the 50%-life.

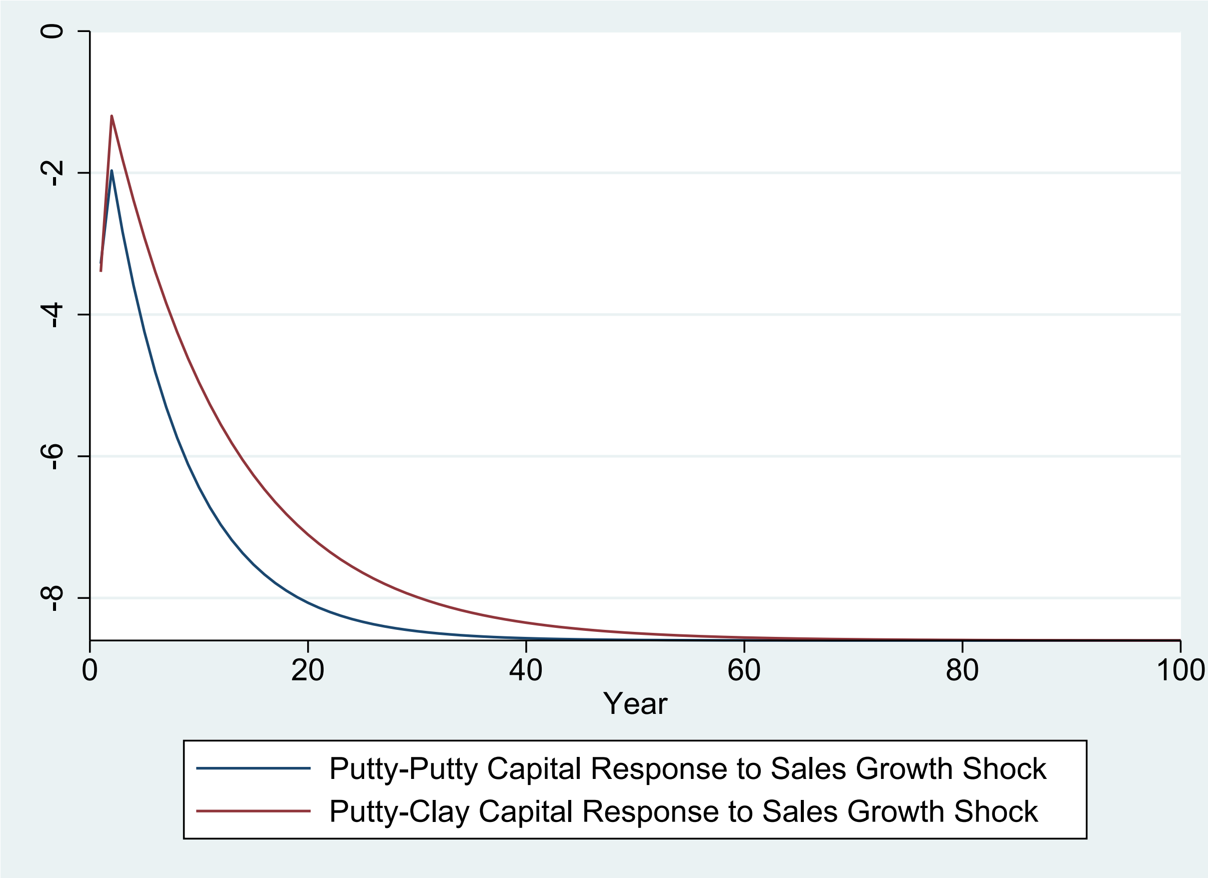
(as in Table E.2) from an accelerator model of investment overestimates the adjustment speed of capital as it ignores the ability of firms to adjust their utilisation of capital. These results provide an explanation for the prolonged lack of investment in the UK economy post-GFC. For example, after a negative capital shock Table E.5 and Figure 4.5 predict a distinct lack of investment in capital stock as firms instead increase their rate of capacity utilisation.

In fact, Figure 4.6 depicts the dynamic path of $k_{j,t}$ following a (permanent) negative 8.6% shock to sales - replicating a drop in output in 2009[30] [31]. In both a putty-putty environment (from Table E.2, which excludes capacity dynamics) and a putty-clay environment (from Table E.5, which includes capacity dynamics), following the (permanent) negative sales growth shock capital steadily falls to a permanently lower level in the long-run. Moreover, this permanently lower long-run level of capital equals the now permanently lower level of sales (since sales is the long-run value of capital). Thus, whether capital is putty-putty or putty-clay following a (permanent) negative sales shock capital converges to the same permanently lower level. However, the speed of this adjustment differs - in a putty-putty environment adjustment is quicker due to the faster error-correcting process. Thus, in the immediate aftermath of the GFC capital began a long and slow adjustment towards a permanently lower level - ad adjustment that is even slower if firms face fixed factors of production in the short-run and instead adjust their rate of capacity utilisation. In general, Table E.5 and Figure 4.5 predict that recessionary slumps are followed by prolonged periods of diminished capital investment, as firms make greater use of their existing capital stock. Thus, even after a recession has ended and an economy is in a recovery or boom period the scarring from a recession is still present - and that scarring lasts longer than predicted in traditional accelerator models of investment.

[30] Derived using Equation 4.26 and the system in Equation 4.30, where the latter includes the additional term $\binom{\xi_2^k}{\xi_2^\Omega} y_{j,t} + \binom{\lambda_2^k - \xi_2^k}{\lambda_2^\Omega - \xi_2^\Omega} y_{j,t-1}$.

[31] Data on the drop in output is taken from ONS series L3BN which measures manufacturing period-on-period growth.

Figure 4.6: The Dynamic Response of Capital to a (Permanent) Negative Sales Shock



Note: Figure 4.6 depicts the dynamic response of capital to a sales growth shock in both a putty-putty environment and putty-clay environment. The system GMM from Table E.2 and Table E.5 are used to calculate the impulse response functions.

4.5 Conclusion

The purpose of this chapter is to examine the dynamic investment behaviour of firms. Specifically, this chapter extends the classic accelerator model of investment with error correction found in Mairesse et al. (1999), Bond et al. (2003), Bloom et al. (2007) and Kang et al. (2014) to include a capacity error correction term following Abel (1981). The key contribution of this chapter is to relax the implicit assumption of a putty-putty environment (where factors of production are instantaneously adjustable) in the accelerator model, instead estimating a dynamic investment equation where factors of production are fixed. In this putty-clay environment, firms adjust their rate of capacity utilisation (as their stock of capital and labour are fixed) in order to meet demand. Assuming a putty-clay framework augments the standard accelerator model with a capacity error correction term. The key finding from this study is that excluding capacity dynamics (in the form of a capacity error correction term) from the standard accelerator model of investment over-estimates the adjustment speed of capital back to its long-run equilibrium value. Firms faced with fixed factors of production instead change their rate of capacity utilisation in the short-run. In other words, excluding capacity dynamics from an accelerator model of investment underestimates the time it takes capital to return to its long-run equilibrium value. This provides an explanation for sluggish investment following the GFC (and recessions in general). In addition, these results are robust to the inclusion of a series of (directly measurable) investment constraints.

Chapter 5

Conclusion

5.1 Concluding Remarks

This thesis has demonstrated the importance of utilising firm-level survey data. Chapter 2 provides an outline of the information contained in the Confederation of British Industry (CBI) suite of business surveys. It demonstrates the large number of economic variables measured, the large timespan of data, the large number of participating firms and their continuity over multiple survey waves. In addition, matching this large dataset to other data sources (such as company accounts data like Bureau van Dijk FAME or Office of National Statistics (ONS) business surveys) yields further insights. Matching the CBI dataset to Bureau van Dijk FAME dataset is fairly straightforward (using firm names as a matching key) and is implemented by Bureau van Dijk using a modified trigram decomposition. Matching to the Inter-Departmental Business Register (IDBR) is implemented by the IDBR support team at ONS using a token decomposition to create a propensity matching score - this yields a set of definite, multiple and no matches. Selection of a unique match among the set of multiple matches is based on a decision rule derived explicitly to match the CBI dataset to the Annual Business Survey (ABS), the Monthly Business Survey (MBS) and the Quarterly acquisitions and disposals of Capital Assets Survey (QCAS). The match rates of the CBI dataset to the Bureau van Dijk FAME dataset are around 50% - with similar (but lower) match rates to the ABS, MBS and QCAS (except for financial services firms in the CBI dataset). These successful match rates enhance the CBI dataset by matching survey responses (which provide insight into firm-decision making) with company accounts data (i.e. actual outcome data). This matching exercise is a precursor to testing the directional accuracy of firm output and employment forecasts, as now the survey-based ex-ante forecasts can be compared with the corresponding actual outcome from company accounts. Using the Hanssen and Kuipers discriminant and a

Pearson Chi-Square test, output and employment forecasts of firms in the manufacturing and mining and distributive trades sectors have value. However, this is not the case in either the service or financial services sector.

Even if a researcher is ambivalent about using qualitative survey data, Chapter 3 provides a new and novel method for quantifying firm-level survey data into a quantified industry-level expected growth series. This meta-modelling quantification approach enhances existing quantification strategies (such as the simple balance statistic or Anderson-Pesaran regression approach) by using non-constant and non-symmetric quantification to account for structural change. Furthermore it limits the ability of researchers to make arbitrary decisions (a drawback with some existing quantification techniques) which can lead to misspecification issues. In practice, it also yields a more reliable measure of industry-level expected output growth, output disagreement and output uncertainty than the simple balance statistic (for example). These quantified series can be used in a straightforward Vector Autoregression (VAR) model (along with actual output growth) to examine the dynamic interactions between each series. Output uncertainty shocks have a negative impact on both expected and actual output (in levels) - both decrease to a permanently lower long-run level circa 0.2% to 0.6% below its initial value. Following a one standard deviation expected output shock, actual output increases to a permanently higher long-run value which is circa 1.2% to 2.6% higher than its pre-shock value. In each sector, both expected and actual output converge to the same long-run value. However, convergence is slow and non-monotonic - in contrast to full-information rational expectations (where the response of actual output would mirror the expected output response after one quarter). Following a one standard deviation actual output shock expected output increases to a permanently higher value circa 0.7% to 1.8% higher than its pre-shock values. Using a Beveridge-Nelson trends decomposition the impact of actually observed output uncertainty shocks on the UK economy can be analysed. For example, shocks to output uncertainty and output disagreement caused trend output in the manufacturing and mining sector to be circa 2.5% to 4.5% lower than it would have been in the absence of shocks through 2008-2012, and circa 1% to 2% lower at the end of the sample. Comparably large effects for output uncertainty and output disagreement are observed in the service and distributive trades sectors.

Chapter 4 shows the benefits which arise from matching the CBI dataset to company accounts data (specifically, the Bureau van Dijk FAME dataset). The CBI dataset provides a direct measure of the rate of capacity utilisation (a variable not directly available from company accounts data), while the Bureau van Dijk FAME dataset provides observed data on investment (as well as sales and cash-flow). Using and updating the Abel (1981) framework, Chapter 4 specifies an investment equation using putty-clay technology. Assuming technology is putty-putty (i.e. factors of production can be freely adjusted at all times) is based on unrealistic assumptions. Moreover, a key implication of putty-putty technology (that there are no under-utilised resources) is not borne out by CBI survey data. With putty-clay technology factors of production are fixed in the short-run. Capital can be fixed in the short-run (for example) as it takes time to purchase, install and train employees to use new machinery. With factors fixed in the short-run, firms are unable to adjust their capital stock in response to demand. Instead, firms alter their rate of capacity utilisation (i.e. increase the intensity with which they use their stock of capital). This is just a short-run solution, in the long-run firms are free to adjust their capital stock. However, the speed of this adjustment is now slower than under the assumption of putty-putty technology. This is confirmed by estimating an accelerator model of investment first with putty-putty technology and then with putty-clay technology. Both investment specifications contain a capital error correction term (which gives the speed of adjustment of capital back to its long-run equilibrium value). But only the specification with putty-clay technology has a capacity error correction term. Estimating these specifications (using system GMM) confirms the predicted results - the adjustment of capital back to its long-run value is slower when firms adjust their rate of capacity utilisation. These results are robust to the inclusion of a series of firm-level investment constraints (such as uncertainty, insufficient finance and poor proposed return on investment). Thus, assuming putty-putty clay technology overestimates the speed with which capital returns to its long-run value. This provides an explanation for the prolonged lack of investment in the UK economy post-GFC. For example, following a negative system-wide shock (where there is both a simultaneous capital and capacity utilisation shock) capital slowly returns to its long-run value as firms instead increase their rate of capacity utilisation. Similarly, following a (permanent) negative exogenous sales shock capital steadily falls to a permanently lower level in the long-run with the speed of adjustment in a putty-clay environment being quicker due to the faster error-correcting process. Thus, in the immediate aftermath of the GFC capital began a long and slow adjustment towards a permanently lower level - an adjustment that is even slower if firms face fixed factors of production in the short-run and instead adjust their rate of capacity utilisation.

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Appendix A

Selected Responses to the Confederation of British Industry (CBI) Suite of Business Surveys

This appendix provides a summary of the properties of the data relating to same key business cycle features - specifically movements in output, investment and inventories.

A.1 Selected Responses to the Industrial Trends Survey (ITS)

A.1.1 Output

Output in the ITS is defined as volume of production. Firms are asked (excluding seasonal variations) for their output expectation and realisation (i.e. quarterly forecast and backcast) - to which firms can respond up, same or down. The proportion of firms each quarter responding up, same and down is plotted in Figure A.1a. While the proportion of firms selecting same clearly dominates prior to the financial crisis, this alters during the financial crisis and Great Recession when the proportion of firms selecting down sharply increases (with a corresponding decline in the proportion of firms selecting up or same). Post the Great Recession the proportion of firms selecting up peaks and despite a dip during 2015 remains elevated above pre-financial crisis levels until 2019. Correspondingly, the proportion of firms selecting down troughs during this period but nevertheless this period also represents a return to the domination of the proportion of firms responding same. The ongoing Brexit negotiations and 2019 UK general election correspond with a steady increase (decrease) in firms selecting down (up). This trend is reversed in 2020Q1 but the onset of the COVID-19 pandemic results in a dramatic increase of firms selecting down. This period represents the largest gap between the proportions of firms reporting up and down.

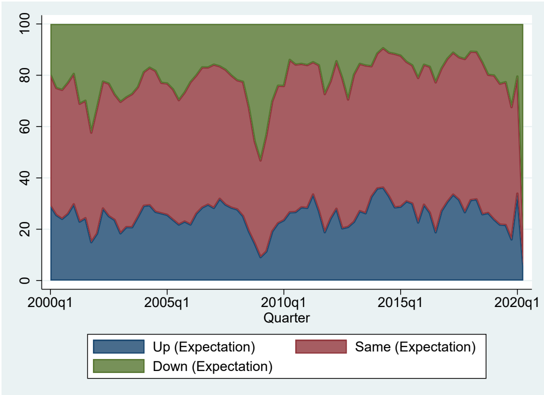
Figure A.1b and Figure A.1c compare the proportion of firms selecting up and down for output expectations and realisations. While the correlation between the proportions for firms selecting up is 0.7 and 0.88 for firms selecting down there are some differences between the series. For example, for much of the sample period the proportion of firms retrospectively selecting down for quarter t exceeds the proportion of firms in the previous period when looking forward selecting down for quarter t - indicating (perhaps) a degree of over-optimism on the part of firms. In fact, there also appears to be a degree of pessimism around the financial crisis and Great Recession as firms underestimate their output volume. The onset of the COVID-19 pandemic results in a sharp divergence (unsurprisingly) between expectations and realisations - for firms selecting both up and down.

In addition to questions regarding output expectations and realisations, firms in the ITS provide information each quarter on factors likely to limit their output over the next three months. The list of potential factors (excluding n/a) are orders or sales, skilled labour, other labour, plant capacity, credit or finance, materials or components and other (details of which are not provided). Firms are not asked to rank these factors but they can select more than one. Out of the total number of factors selected each quarter the proportion of these responses attributable to each individual factor is depicted in Figure A.1d. Only firms selecting same or down to the output expectation question are included in Figure A.1d. Throughout the sample orders or sales is always the dominant factor limiting future output with the proportion of firms selecting this factor rarely falling below 60%. The time paths of the proportion of firms selecting plant capacity and skilled labour as the main factor limiting future output are broadly similar - that is, falling to a trough during the financial crisis and Great Recession and continuing to rise towards the end of the sample (but sharply decrease at the onset of the COVID-19 pandemic). The proportion of firms selecting credit or finance as the main factor limiting future output peaks during financial crisis and Great Recession before slowly declining back to its original level.

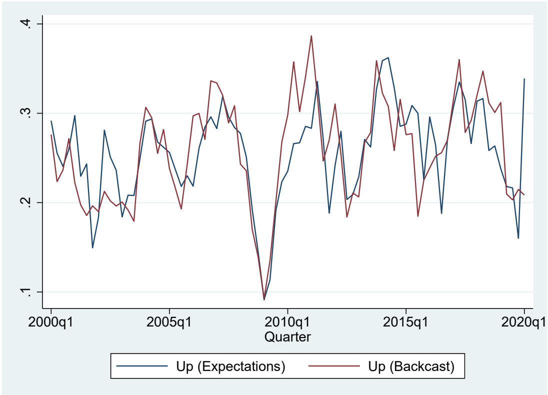
A.1.2 Investment

Questions regarding investment fall into three categories in the ITS; the expectations and realisations of capital expenditure, factors positively influencing investment intentions and factors likely to limit future investment. Investment is categorised into four components in the ITS dataset - land and buildings; plant and machinery; product and process innovation

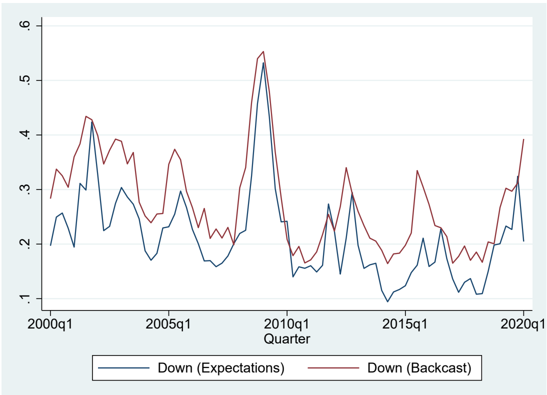
Figure A.1: ITS: Questions Related to Output



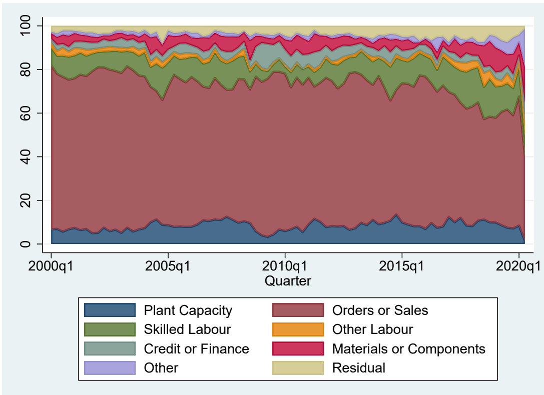
(a) Proportion of Firms Responding Up, Same, Down



(b) Expectation and Realisation of Output (Up)



(c) Expectation and Realisation of Output (Down)



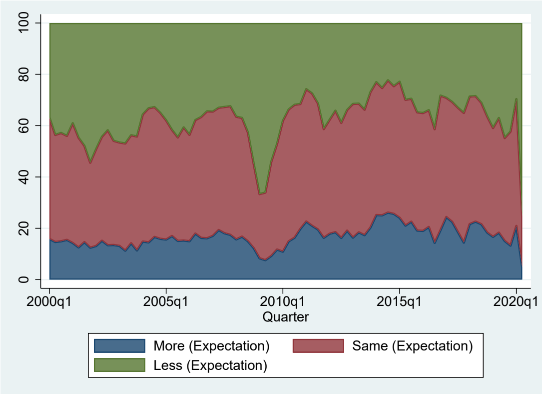
(d) Factors Limiting Future Output

and training and retraining. Specifically, firms are asked if they expect to authorise more, the same or less expenditure in the next twelve months than in the previous twelve months for each of these components. The proportion of firms each quarter responding more and less to each of these questions is plotted in Figure A.2a to Figure A.2d. One common trend is obvious among the investment intentions of firms in the ITS: a reduction in capital expenditure during the financial crisis and Great Recession. Across each component of investment the proportion of firms selecting less increases while the proportion selecting more decreases. In addition, the proportion of firms selecting less for capital expenditure on land and buildings and plant and machinery sharply increases during the COVID-19 pandemic - while for product and process innovation and training and retraining the proportion of firms selecting more decreases sharply. With respect to capital expenditure on land and buildings and plant and machinery the proportion of firms selecting less usually exceeds those selecting more (apart from a brief period c.2014-2015) - although the proportion of firms selecting more post the Great Recession (in general) exceeds its pre-crisis levels. In contrast, the proportion of firms selecting more for capital expenditure on both product and process innovation and training and retraining usually exceeds the proportion of firms exceed less - with the gap between the two series widening post-Great Recession as the proportion of firms selecting less declines (except towards the end of the sample).

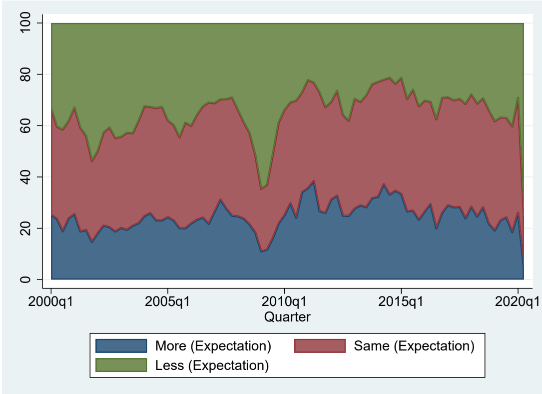
Potential factors positively influencing the decision to invest included in the ITS dataset are (excluding the non-applicable option): to expand capacity, to increase efficiency, for replacement and other (details of which are not provided). In fact, in the ITS firms are asked to rank these factors in order of importance to their decision-making - although this study will focus on the primary factors (that is, those selected as number one). The proportion of firms each quarter selecting each of these factors (including those selecting N/A) as their primary factor is plotted in Figure A.2e. Only firms selecting up to at least one of the investment expectation questions is included in Figure A.2e. Throughout the sample period investing to increase efficiency is usually the main factor selected by firms as a reason for investing - although the proportion of firms selecting this option declines throughout. This is in contrast to the proportion of firms selecting for replacement which remains fairly constant throughout the sample while the proportion of firms selecting to expand capacity increases notably after the financial crisis and Great Recession (during which the proportion of firms selecting this factor declined). The proportion of firms selecting either the other or non-applicable option rarely exceeds 10%.

Potential factors negatively influencing the decision to invest included in the ITS dataset are (excluding the non-applicable option): inadequate net return on proposed investment, shortage of internal finance, inability to raise external finance, cost of finance, uncertainty about demand, shortage of labour and other (details of which are not provided). In fact, in the ITS firms are asked to rank these factors in order of importance to their decision-making - although this study will focus on the primary factors (that is, those selected as number one). The proportion of firms each quarter selecting each of these factors (including those selecting N/A) as their primary factor is plotted in Figure A.2f. Only firms selecting down or same to at least one of the investment expectation questions is included in Figure A.2f. Throughout the sample period uncertainty about demand is always the primary limiting factor influencing investment - peaking at above 60% of firms during the financial crisis and Great Recession. In fact, the proportion of firms selecting this as the main factor limiting investment only falls below 40% towards the end of the sample. The proportion of firms selecting inadequate net return as the main factor limiting investment fluctuates around 30% prior to the financial crisis before falling to below 20% during the financial crisis and Great Recession. The proportion of firms selecting a shortage of internal finance as the main factor limiting investment peaks at just under 18% during the financial crisis and Great Recession before reverting to levels prior to the financial crisis (with a sharp increase at the onset of the COVID-19 pandemic) while the time path of shortage of labour is the opposite (qualitatively speaking).

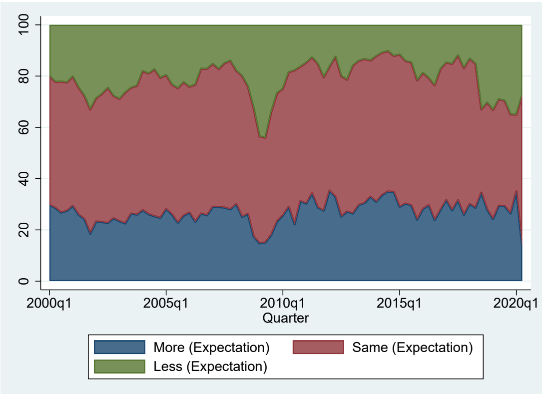
Figure A.2: ITS: Questions Related to Investment



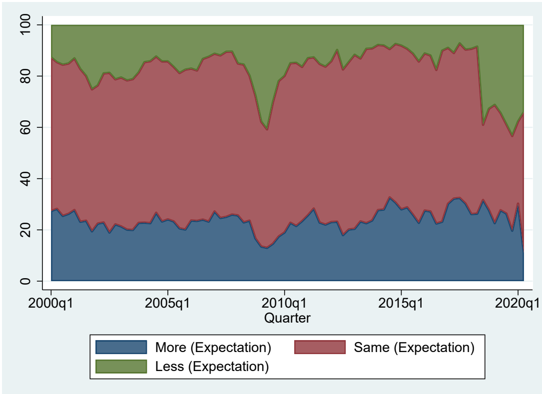
(a) Land and Buildings



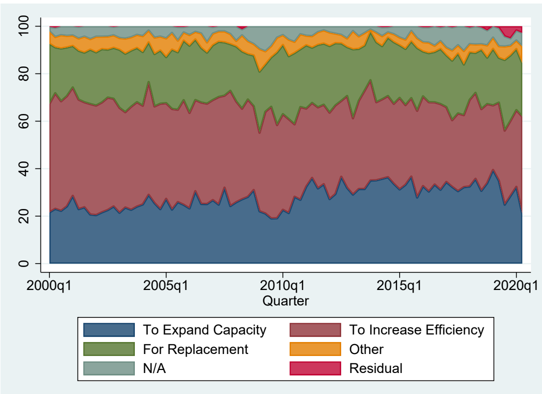
(b) Plant and Machinery



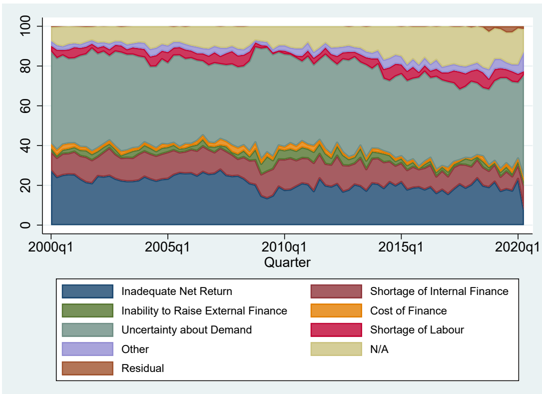
(c) Product and Process Innovation



(d) Training and Retraining



(e) Factors Encouraging Investment



(f) Factors Limiting Investment

A.1.3 Inventories

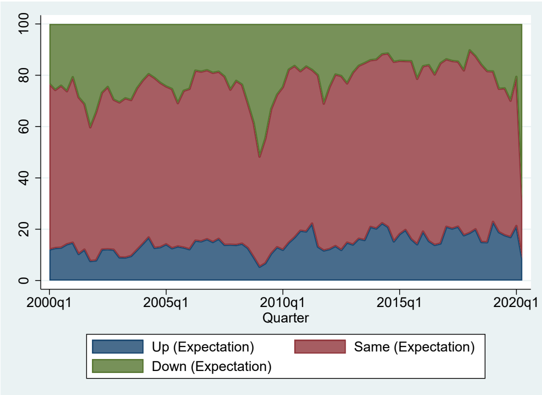
Inventories are categorised into three components in the ITS - raw materials and bought-in-supplies; work in progress and finished goods. Specifically, firms are asked (excluding seasonal variations) for their expectation and realisation (i.e. quarterly forecast and back-cast) of each inventory component - to which firms can respond up, same or down. The proportion of firms each quarter responding up and down to each of these questions is plotted in Figure A.3a to Figure A.3i. Expectations of across the three inventory categories demonstrate similar trends - the proportion of firms selecting down dominate prior to the financial crisis; during the financial crisis and Great Recession the proportion of firms selecting down increases and the proportion selecting up decreases; post-Great Recession there is a lack of stability in the dominance of firm responses (although the proportion of firms selecting up has increased since the start of the sample while the proportion of firms selecting down has decreased) while the COVID-19 pandemic resulted in a sharp increase in the proportion of firms selecting down (and a corresponding fall in the proportion of firms selecting up). Firms in the ITS have a (relatively) mixed record with regards to predicting their future inventory levels. The correlation between the proportions of firms selecting up is 0.73, 0.64 and 0.47 for raw materials and bought-in-supplies, work in progress and finished goods expectations and realisations (respectively). In contrast, firms which select down are good predictors with a correlation of 0.9, 0.88 and 0.86 between the proportion of firms selecting down for raw materials and bought-in-supplies, work in progress and finished goods expectations and realisations (respectively) with minimal discrepancies between these proportions.

A.2 Selected Responses to the Remaining Surveys

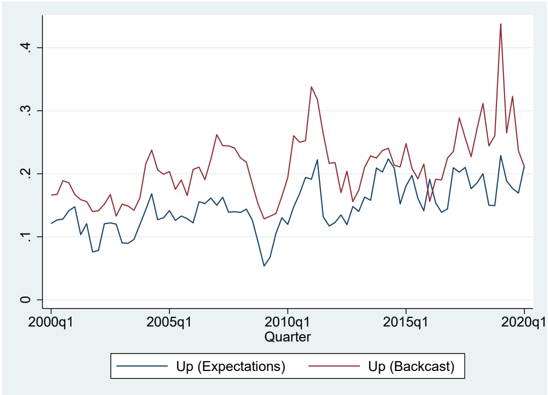
A.2.1 Service Sector Survey (SSS)

Output in the SSS is defined as volume of business. Firm responses are depicted in Figure A.4a which follows a path similar to Figure A.1a. Figure A.4b and Figure A.4c compare the proportion of firms selecting up and down for output expectations and realisations with a correlation of 0.82 for firms selecting up and 0.9 for firms selecting down. While there are some discrepancies between these proportions for each response, on the whole service firms appear to be relatively good predictors of their future business volume. Figure A.4d examines the factors limiting output - note the additional options of domestic and overseas competition (and the lack of materials or components option). Only the time paths of future output limited by level of demand or sales and future output limited by availability of professional staff demonstrate any noticeable movement. In particular, the proportion of firms selecting the former increases during the financial crisis and Great Recession before slowly returning to its original level while the latter follows the mirror image (qualitatively speaking). Actually, the time path of future output limited by the availability of clerical staff follows a similar (but less pronounced) path to output limited

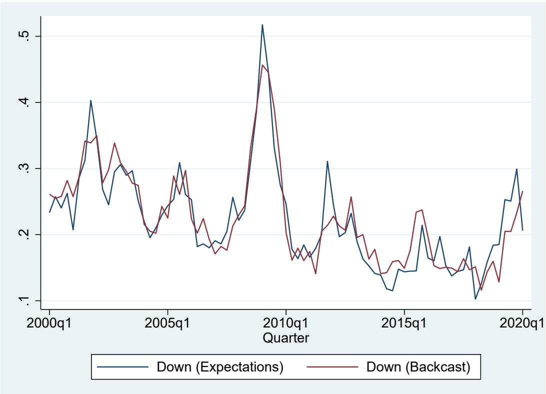
Figure A.3: ITS: Questions Related to Inventories



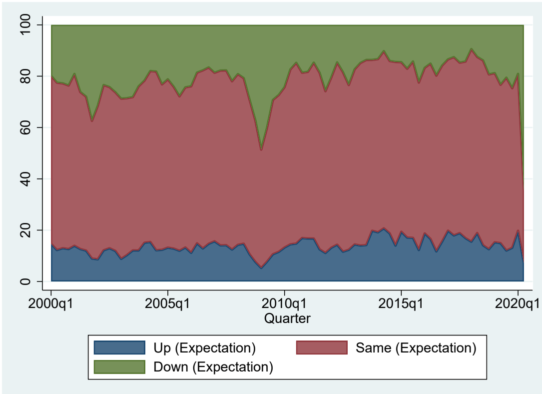
(a) Raw Materials and Bought-in-Supplies



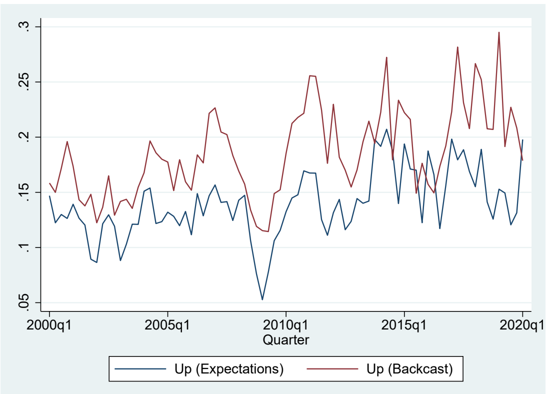
(b) Expectation and Realisation of Raw Materials and Bought-in-Supplies (Up)



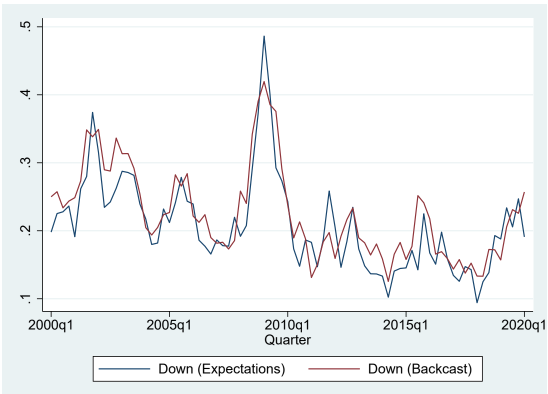
(c) Expectation and Realisation of Raw Materials and Bought-in-Supplies (Down)



(d) Work in Progress



(e) Expectation and Realisation of Work in Progress (Up)

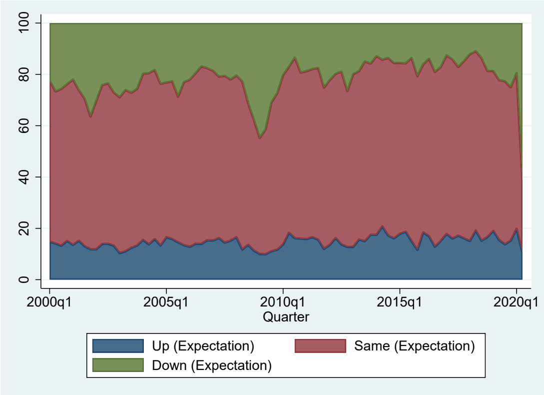


(f) Expectation and Realisation of Work in Progress (Down)

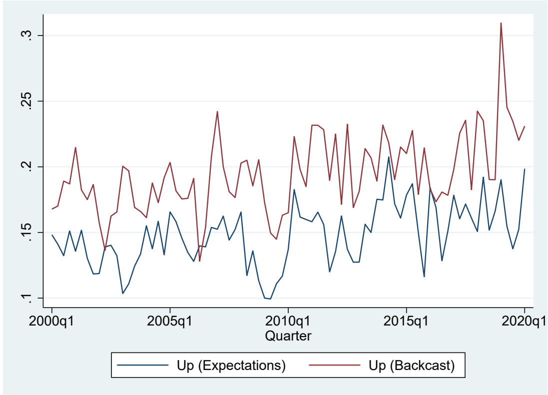
by the availability of professional staff.

The categorisation of investment in the SSS is (marginally) different to the ITS - land and buildings; vehicles, plant and machinery; information technology and training and retraining. Furthermore, capital expenditure on training and retraining refers to the three-month expectation and realisation (rather than twelve-month expectation only).

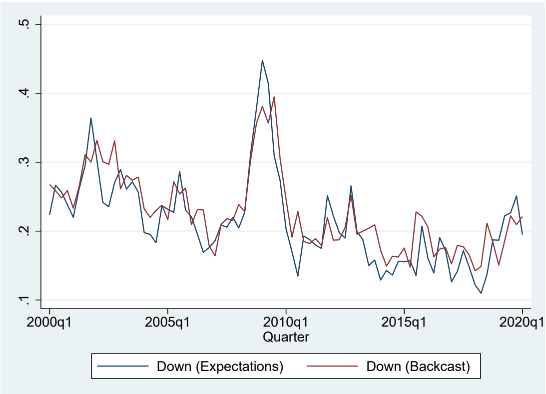
Figure A.3: ITS: Questions Related to Inventories (Continued)



(g) Finished Goods



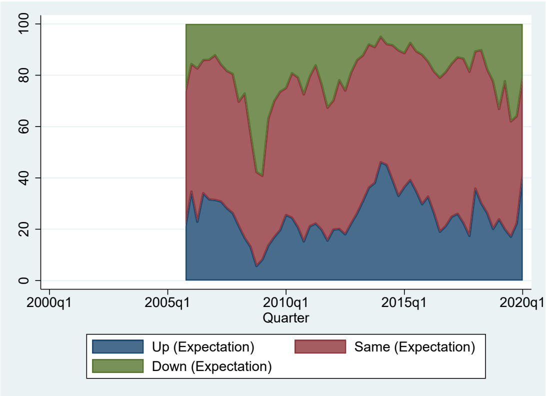
(h) Expectation and Realisation Finished Goods (Up)



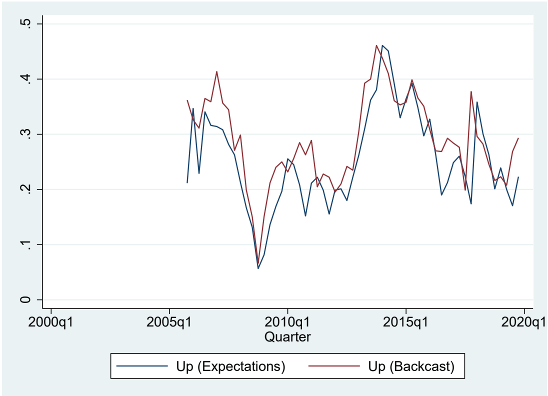
(i) Expectation and Realisation Finished Goods (Down)

Firm responses are depicted in Figure A.5a to Figure A.5d each broadly following a path (qualitatively) similar to their ITS counterpart. Figure A.5e and Figure A.5f compare the proportion of firms selecting more and less for capital expenditure on (re)training expectations and realisations with a correlation of 0.82 for firms selecting more and 0.89 for firms selecting less. Figure A.5g depicts service firm responses to their expansion intentions over the next twelve months (vis-à-vis the preceding twelve months). The decision to expand is the predominate choice among service firms on either side of the financial crisis and Great Recession - events during that particular time frame clearly had a significant impact on expansion intentions (which take four years to recover to their pre-crisis level). Figure A.5h examines the factors encouraging investment - note the additional options to provide new services, to reach new customers, euro-related and e-business related. Throughout the sample period investing to increase efficiency and for replacement are consistently ranked as the main factor positively influencing investment with investing for replacement being predominant during the financial crisis and Great Recession. The proportion of firms selecting investment for expand capacity decreases during the financial crisis and Great Recession before recovering. The remaining time-

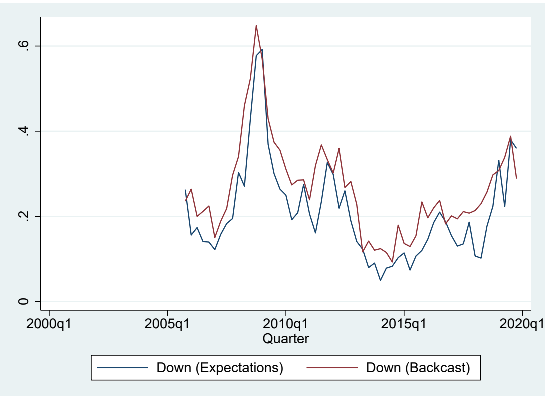
Figure A.4: SSS: Questions Related to Output



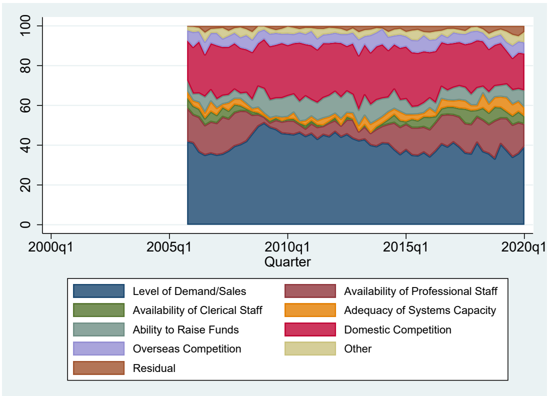
(a) Proportion of Firms Responding Up, Same, Down



(b) Expectation and Realisation of Output (Up)



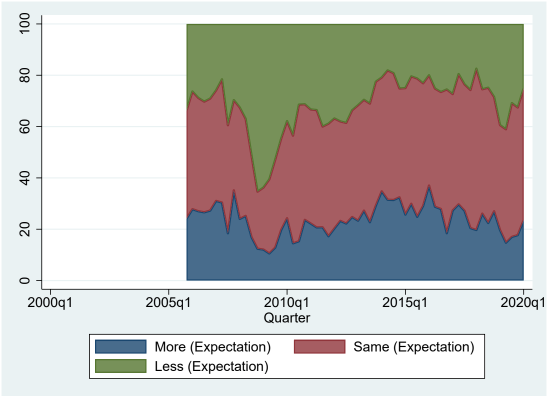
(c) Expectation and Realisation of Output (Down)



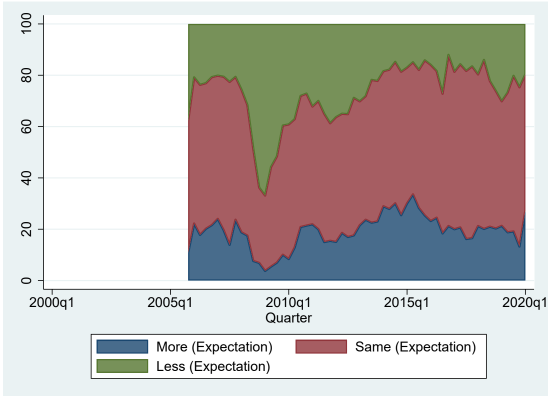
(d) Factors Limiting Future Output

paths do not follow any discernible pattern except for investment to provide new services, which decreases during the financial crisis and Great Recession before rising and exceeding pre-crisis levels. Figure A.5i examines the factors limiting investment. Throughout the sample period uncertainty about demand or business prospects is always the dominant factor limiting investment. In fact, the proportion of firms selecting this as the main factor increases during the financial crisis and Great Recession and only slowly declines before beginning to increase again by the end of the sample. The remaining time paths do not demonstrate any discernible pattern save for investment limited by shortage of labour, investment limited by cost of finance and investment limited by inability to raise external finance. The first falls during the financial crisis and Great Recession before slowly recovering to pre-crisis levels; the second falls during the financial crisis and Great Recession and remains lowered for the remainder of the sample while the third increases during the financial crisis and Great Recession before slowly returning to pre-crisis levels.

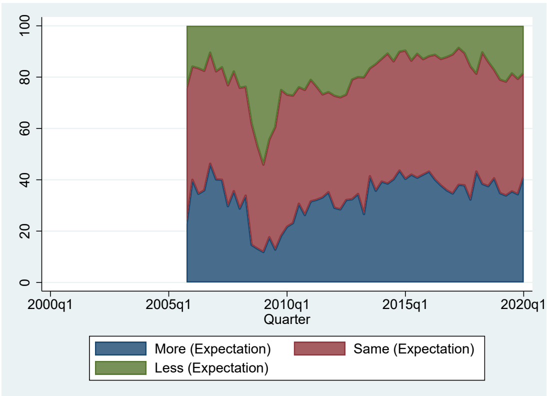
Figure A.5: SSS: Questions Related to Investment



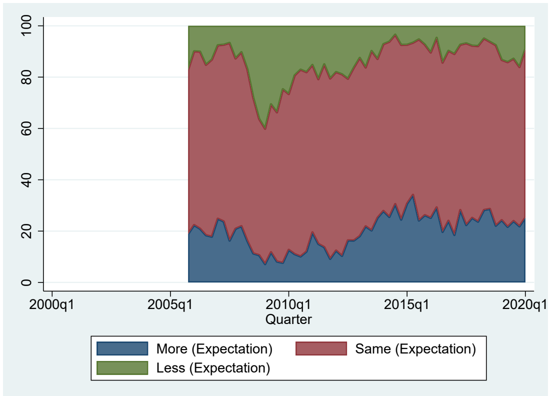
(a) Land and Buildings



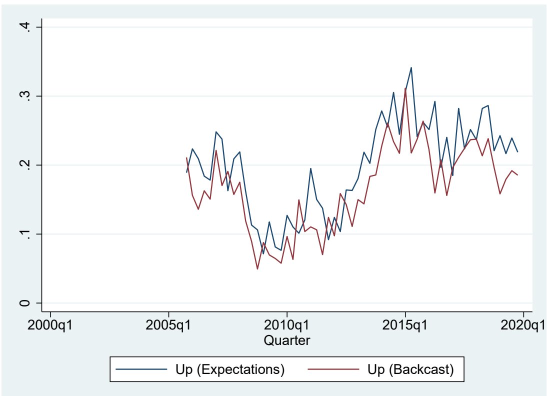
(b) Vehicles, Plant and Machinery



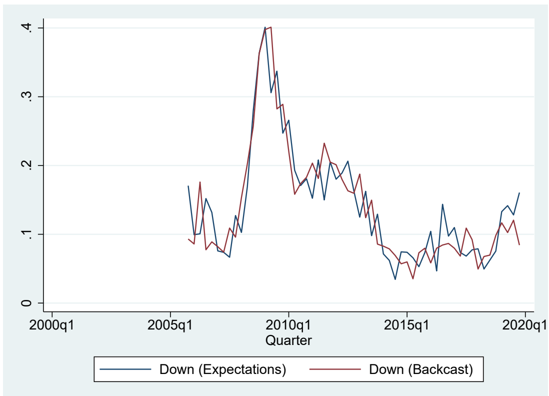
(c) Information Technology



(d) Training and Retraining



(e) Expected and Realised Capital Expenditure on Training and Retraining (More)

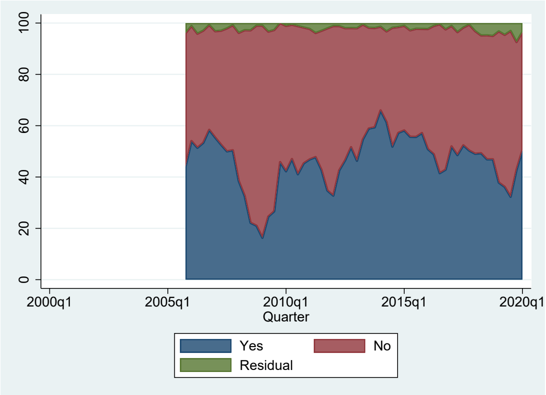


(f) Expected and Realised Capital Expenditure on Training and Retraining (Less)

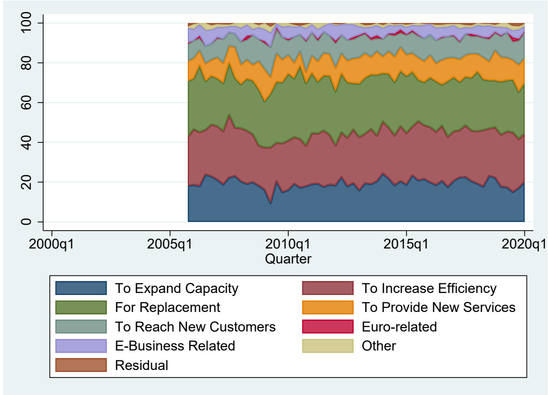
A.2.2 Distributive Trades Survey (DTS)

Output in the DTS is defined as volume of sales. Firm responses are depicted in Figure A.6a which follows a path similar to Figure A.1a. Figure A.6b and Figure A.6c compare the proportion of firms selecting up and down for output expectations and realisations with a correlation of 0.75 for firms selecting up and 0.83 for firms selecting down. Again,

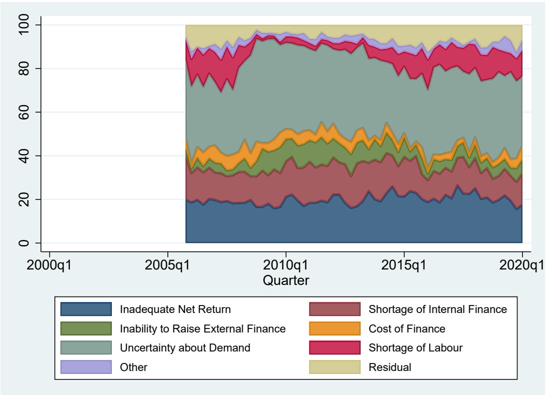
Figure A.5: SSS: Questions Related to Investment (Continued)



(g) Expansion Intentions



(h) Factors Encouraging Investment



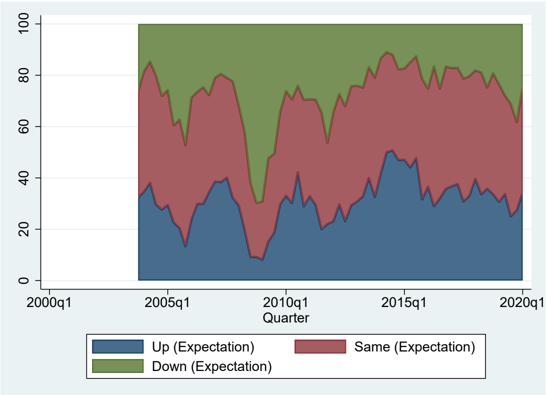
(i) Factors Limiting Investment

while there are discrepancies between the proportions firms in the DTS appear relatively good predictors of future sales volume.

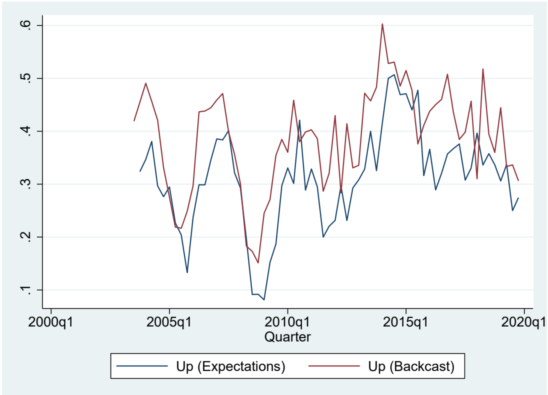
The DTS does not categorise investment into components opting instead to ask firms if they expect to authorise more, the same or less capital expenditure in the next twelve months than authorised in the past twelve months. These investment intentions are depicted in Figure A.6d which indicates a sharp increase in firms intending to invest less during the financial crisis and Great Recession. In fact, throughout the sample period the proportion of firms selecting less usually exceeds those selecting more (a notable exception being c.2014-2015). Questions regarding the factors influencing the investment decision are absent from the DTS.

The DTS does not categorise inventories into components but asks firms if their position with regard to their volume of stocks (in relation to expected sales) for the current month and expectations for the following month is too high, adequate or too low compared with those in the same month the previous year. Figure A.6e and Figure A.6f indicate that the vast majority of firms in the DTS feel their volume of stocks are adequate with very few expressing concerns they are too low.

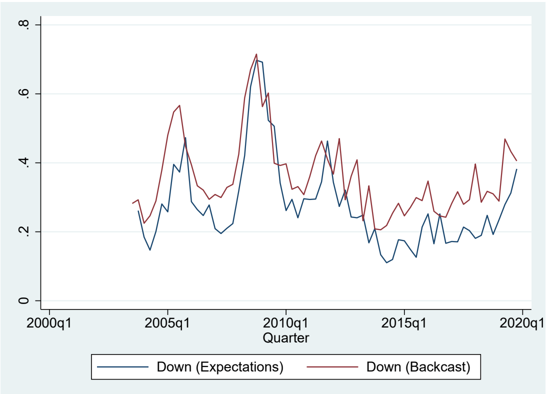
Figure A.6: DTS: Survey Responses



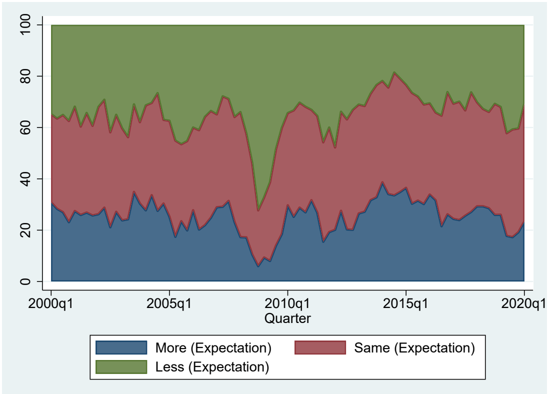
(a) Proportion of Firms Responding Up, Same, Down (Output Expectations)



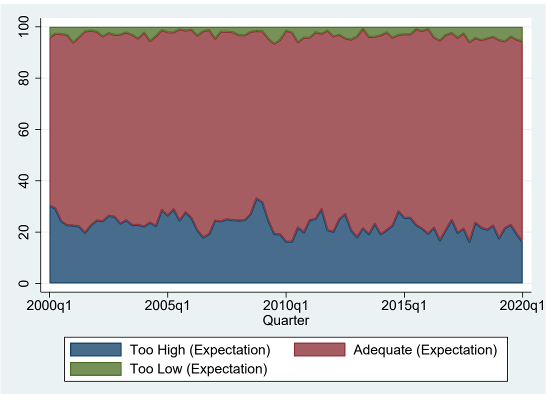
(b) Expectation and Realisation of Output (Up)



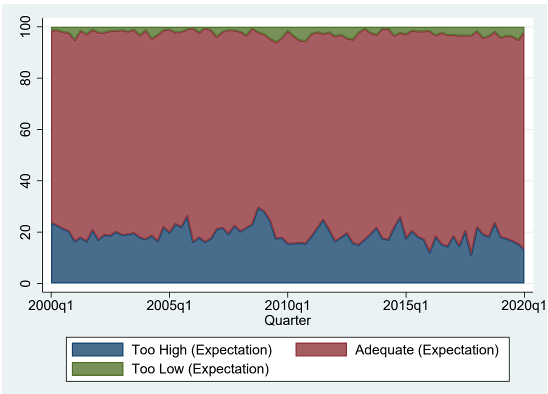
(c) Expectation and Realisation of Output (Down)



(d) Investment Intentions



(e) Volume of Stocks (Current Month)

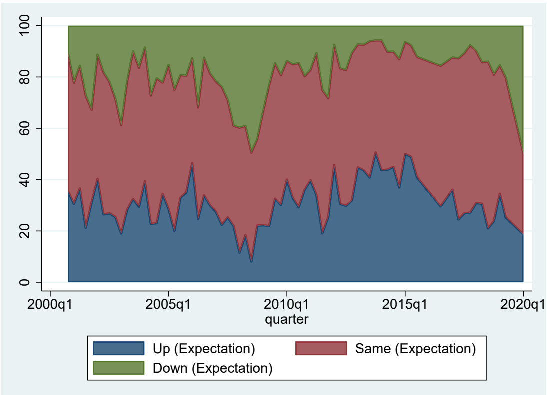


(f) Volume of Stocks (Next Month)

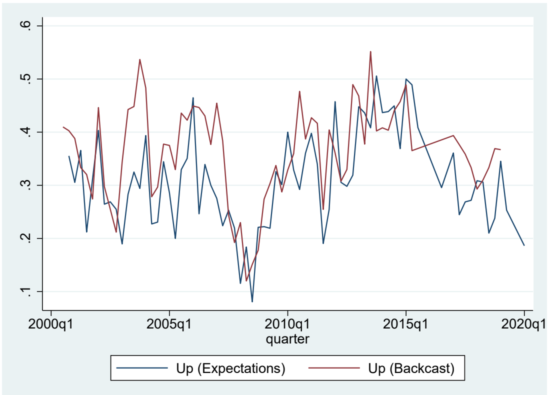
A.2.3 Financial Services Sector (FSS)

Output in the FSS is defined as volume of business. Firm responses are depicted in Figure A.7a which follows a path similar to Figure A.1a. Figure A.7b and Figure A.7c compare the proportion of firms selecting up and down for output expectations and realisations with a correlation of 0.61 for firms selecting up and 0.81 for firms selecting down. However, there are (at times) substantial differences in the time paths of the proportions. Accordingly, it seems that firms in the FSS are at best mediocre predictors of their future volume of business. Figure A.4d examines the factors firms have ranked as number one in limiting their volume of business - note the additional options of level of staff turnover, ability to raise funds (of which ability to raise capital and availability of wholesale funds), competition (with options specifying domestic and overseas competition) and statutory legislation and regulation. The time paths of the proportion of firms selecting factors limiting future output appear to follow no discernible pattern. For example, none of the time paths appear to be overly affected by the financial crisis or Great Recession.

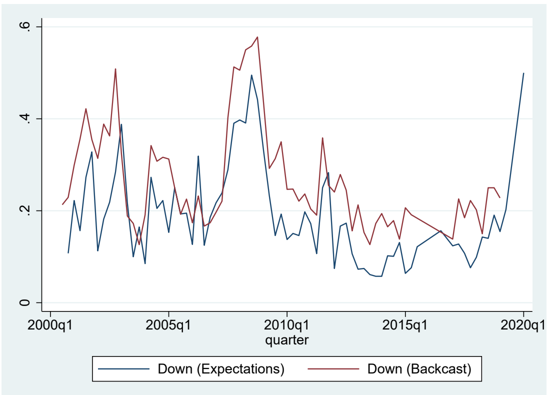
Figure A.7: FSS: Questions Related to Output



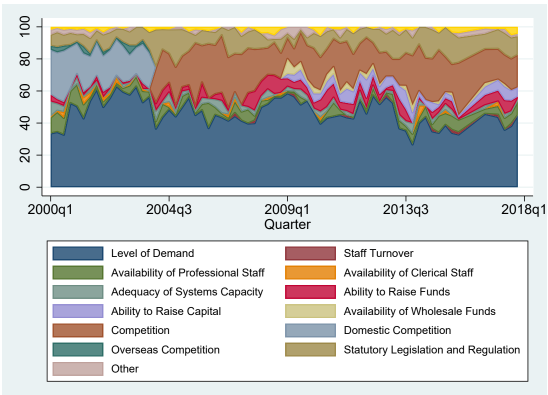
(a) Proportion of Firms Responding Up, Same, Down



(b) Expectation and Realisation of Output (Up)



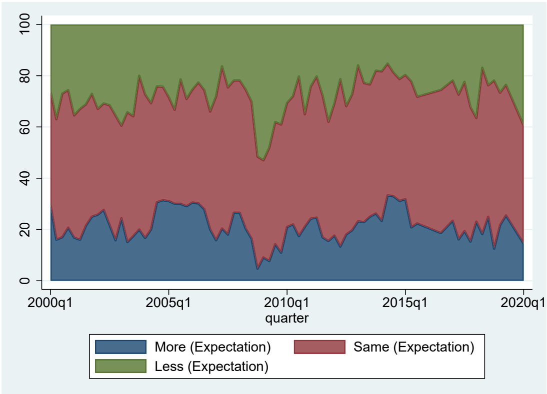
(c) Expectation and Realisation of Output (Down)



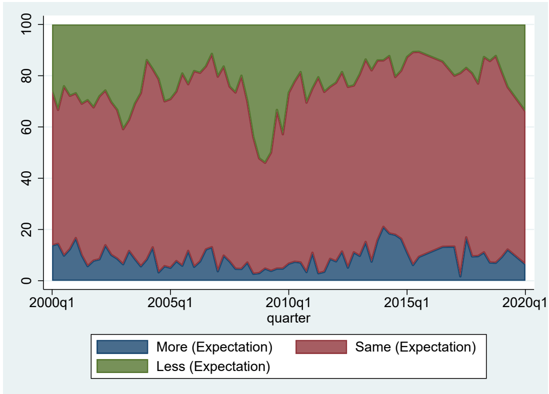
(d) Factors Limiting Future Output

The categorisation of investment in the FSS is identical to the SSS (in all respects). Firm responses are depicted in Figure A.8a and Figure A.8d each broadly following a path (qualitatively) similar to their ITS counterpart. Figure A.8e and Figure A.8f compare the proportion of firms selecting more and less for capital expenditure on (re)training expectations and realisations with a correlation of 0.71 for firms selecting more and 0.85 for firms selecting less. Figure A.8g examines the factors firms have ranked as number one in encouraging investment. The time paths of the proportion of firms selecting factors positively affecting investment appear to follow no discernible pattern. Figure A.5i examines the factors firms have ranked as number one in limiting investment. The time paths of the proportion of firms selecting factors limiting investment appear to follow no discernible pattern.

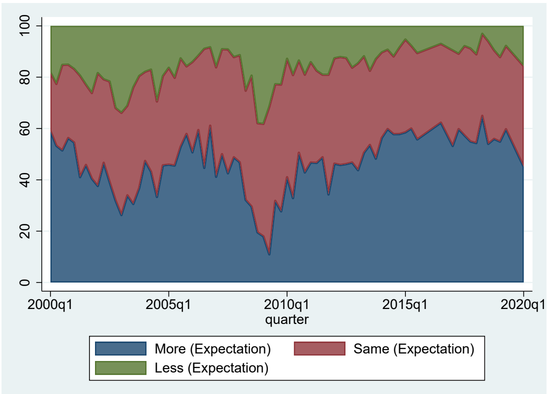
Figure A.8: FSS: Questions Related to Investment



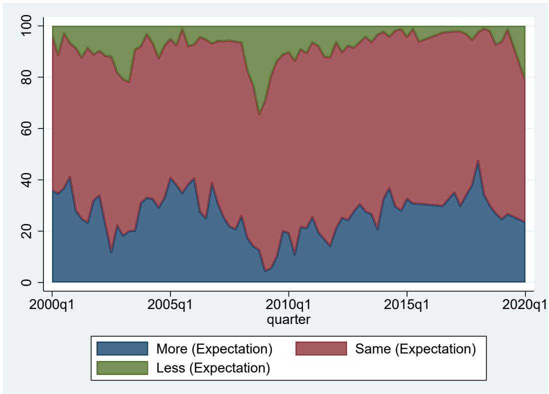
(a) Land and Buildings



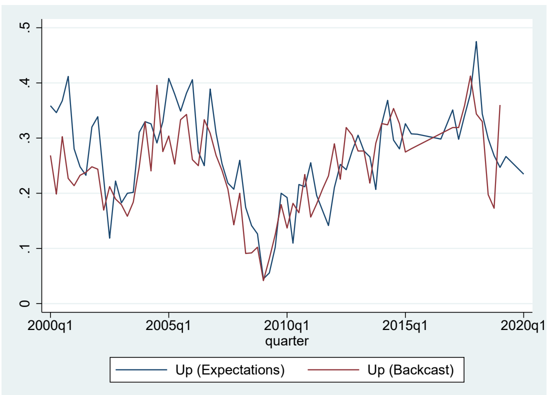
(b) Vehicles, Plant and Machinery



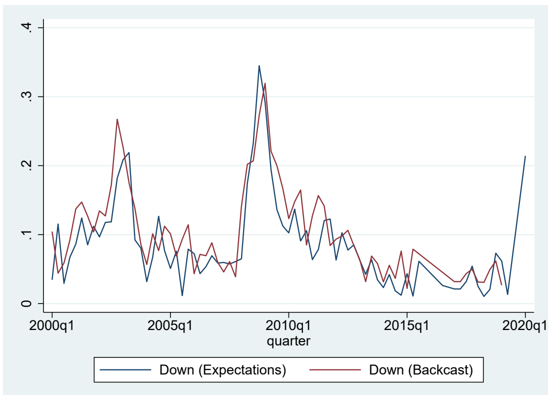
(c) Information Technology



(d) Training and Retraining

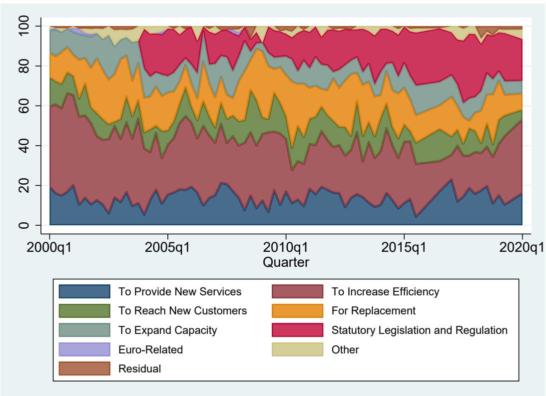


(e) Expected and Realised Capital Expenditure on Training and Retraining (More)

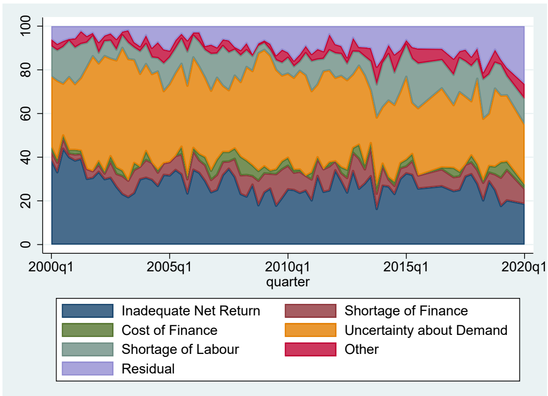


(f) Expected and Realised Capital Expenditure on Training and Retraining (Less)

Figure A.8: FSS: Questions Related to Investment (Continued)



(g) Factors Encouraging Investment



(h) Factors Limiting Investment

Appendix B

The Answering Practices Survey (APS)

Is (qualitative) survey data reliable? This can be answered by looking at firm responses to the Answering Practices Survey (APS) conducted by the CBI between 2009 and 2014. The APS is a questionnaire for participating firms of the ITS, SSS, DTS or FSS where respondents answer a series of questions regarding how they complete their designated survey. This subsection provides an overview of relevant APS results for firms participating in the ITS, SSS, DTS and FSS. Analysing the APS results is important as it provides insight into how firms complete the CBI suite of business surveys - in particular by indicating how firms interpret the survey questions and potential answers (thus mitigating concerns regarding the accuracy of firm survey responses). There is only one set of APS results for each survey type over the period 2009 to 2014. In 2013 186 firms completed the ITS APS, in 2012 120 firms completed the SSS APS, in 2014 85 firms completed the DTS APS and in 2009 55 firms completed the FSS APS.

Table B.1 to Table B.4 provide an overview of how firms complete each survey type. It is clear that each survey is completed by individuals in positions of authority within the firm who would have access to the required information to accurately complete each survey (Table B.1), the vast majority of whom find this an easy process with their major difficulty being irrelevant questions for their firm (Table B.2) and thus are less likely to provide inaccurate answers on the basis of lack of understanding. These findings mitigate against concerns regarding the accuracy of firm survey responses. Nor do firms fail to continually respond to surveys because they find them overly cumbersome or difficult (Table B.3) - rather the primary culprit is a lack of available time on the part of the firm. Unfortunately, details regarding the length of time to complete the survey is only available for the DTS (Table B.4) - however, 57% of distributive trades firms complete their survey within a week of reception implying the majority of DTS survey responses for quarter t are completed in the final week of quarter $t-1$.

Table B.1: APS: Who Completes the Survey?

	ITS	SSS	DTS	FSS
Chairman [a]	60%	55%	46%	60%
Director of Function [b]	24%	24%	18%	16%
Planning and Strategy Director	0%	1%	1%	0%
General Manager [c]	12%	11%	14%	9%
Owner Partner	-	-	7%	-
Manager/Stock Controller	-	-	7%	-
Other	4%	9%	6%	15%

[a] Or managing director, CEO, deputy chairman, vice-president.
[b] Example: finance, marketing, commercial, portfolio, corporate actuary.
[c] Or company secretary/accountant.

Table B.2: APS: Are the Quarterly Surveys Easy to Complete?

	ITS	SSS	DTS	FSS
Yes	69%	79%	-	69%
No; questions not wholly relevant	25%	16%	-	29%
No; inappropriate time horizon	2%	2%	-	2%
No; other	5%	6%	-	5%

Note: Firms can select more than one reason in answering no.

Table B.3: APS: Reason for Firm Non-Response

	ITS	SSS
Length of survey	23%	20%
Lack of time	41%	39%
Number of Other Surveys	10%	12%
Low priority	22%	22%
Absence	27%	18%
Other	5%	3%

Table B.5 details how firms respond to questions asking them to exclude seasonal variation. Except for firms in the DTS, the majority of firms either do adjust for seasonal variation or do not as they are insignificant in their operation. However, while the CBI suite of business surveys asks firms to exclude seasonal variations knowing this information allows for appropriate action to be taken during analysis. Table B.6 and Table B.7 indicate that the vast majority of firms in the ITS and DTS do not adjust their answers to account for national events (such as the Queen's Jubilee or the Olympics or Paralympics) or for

Table B.4: APS: Response Length

	DTS
1-2 Days	26%
3-7 Days	31%
8-12 Days	24%
13-14 Days	16%
Unanswered	3%

adverse or unseasonal weather conditions (DTS firms only). Table B.8 indicates how firms select the answer bins "up" and "down" - in particular, illustrating the percentage of firms which regard "up/down" options as referring to "rising/falling" versus "rising/falling more quickly/slowly" - with the vast majority of firms regarding "up/down" as referring to the former.

Table B.5: APS: Do Firms Adjust for Seasonal Variation?

	ITS	SSS	DTS	FSS
Yes; subjectively	36%	56%	11%	47%
Yes; quantitative procedure	8%	19%	2%	22%
No; not significant	44%	20%	-	25%
No; impossible to measure	10%	4%	-	2%
No; other	1%	1%	-	4%

Note: 87% of firms in the DTS do not adjust for seasonal variation (reasons are not provided).

Table B.6: APS: Do Firms Adjust for National Events?

	ITS	DTS
Yes	6%	4%
No	94%	96%

Table B.7: APS: Do Firms Adjust for Adverse or Unseasonal Weather?

	DTS
Yes	11%
No	89%

Table B.9 to Table B.11 examine firm's understanding of the three-month period referred to in the survey questions. In particular, Table B.9 affirms that the majority of firms (save in the DTS) answer their surveys by comparing quarter t with quarter $t-1$ (as intended by the survey question). The DTS potentially provides different results due to

Table B.8: APS: How do Firms Report Up and Down on Volume Questions?

	ITS	SSS	DTS	FSS
Rise/Fall	92%	83%	-	85%
Rise/Fall more quickly	5%	17%	-	15%
Don't Answer	3%	-	-	-

an earlier question asking firms to compare quarter t with quarter $t-5$. Table B.10 shows the primary influence on trend for firms in the ITS and SSS - with current conditions and recent trends being the most popular answer (and is in fact chosen by a majority of firms in the SSS). Table B.11 shows that most firms in the SSS and FSS measure trend in volume of business as value of income received. Table B.12 examines whether firms in the ITS use values/revenues as an approximation for their volume measures (the majority in the affirmative). Table B.13 examines if DTS firms adjust their value of sales for any price changes to derive their volume of sales measure (the majority do not). Table B.14 asserts that the majority of firms in the ITS do not account for quality improvements while assessing volumes. Table B.15 details how ITS firms which produce heterogeneous products make volume assessments.

Table B.9: APS: How do Firms Understand the Three Month Period

	ITS	SSS	DTS	FSS
Change during period	15%	18%	15%	16%
Compare as whole with previous period	66%	48%	19%	65%
Compare with same period previous year	10%	18%	54%	5%
Combination of above	8%	15%	11%	13%
Other	2%	2%	0%	0%

Table B.10: APS: Primary Influences on Trend over Next Three Months

	ITS	SSS
Current conditions and recent trends	24%	53%
Planned activity within firm	20%	23%
Prediction of trends within sector	9%	-
Prediction of trends in UK/Global economy	3%	3%
Independent of past quarter	-	3%
Other	2%	1%

Note: Firms in the FSS are also asked this question but given different options: 65% of firms selected recent trends, 80% select current conditions, 13% select firm specific factors, 9% select company forecasts/budgets, 20% trends in the, 0% select other.

Table B.16 highlights that the majority of firms in the ITS selecting skilled labour as a constraint on future output are referring to the difficulties in recruiting skilled workers (be

Table B.11: APS: How Firms Measure Trend in Volume of Business

	SSS	FSS
Number of transactions	15%	60%
Number of hours billed	8%	0%
Value of income received	48%	89%
Subjective Assessment	10%	24%
Other	3%	7%

Table B.12: APS: Do ITS Firms use Values/Revenue as an Approximation for Volume?

	ITS
Yes; adjusted for price change	40%
Yes; not adjusted for price change	30%
No	30%

Table B.13: APS: Do DTS Firms Adjust the Value of Sales for any Price Changes to Derive a Volume of Sales Measure?

	DTS
Yes; have sales volume data	7%
Yes; use average price change over year	4%
Yes; use prevailing prices	6%
Yes; make subjective assessment	15%
Yes; other	1%
No	66%

Table B.14: APS: Do ITS Firms Account for Quality Improvements in Assessing Volumes?

	ITS
Yes	26%
No	66%
Don't Know	8%

Table B.15: APS: How ITS Firms Producing an Heterogeneous Product Assess Volumes

	ITS
Subjective Assessment	30%
Quantitative Procedure	12%
Other	2%

Note: The remaining 54% of ITS firms do not produce an heterogeneous product.

they cost or skilled related) while Table B.17 details what these firms regard as skilled labour. Table B.18 indicates that firms have a fairly mixed view as to uncertainty as a constraint on future investment. Table B.19 examines the factors influencing firms in the SSS decisions to expand - with it being clear that sales and expected sales growth are the largest contributors - while Table B.20 details other considerations the firms may have while answering this question. Table B.21 demonstrates the consistency with which firms in the DTS assess the adequacy of stocks in relation to sales for this month and next. Table B.22 to Table B.26 examine the attitudes of firms in the ITS with regards to the capacity questions. While their answers certainly seem insightful it would perhaps be beneficial if questions such as these were in the actual ITS so firm responses could be tracked over time.

Table B.16: APS: What Does Skilled Labour as a Constraint on Future Output Reflect?

	ITS
Current Workforce Only	44%
Difficulties recruiting; cost	1%
Difficulties recruiting; availability	31%
Difficulties recruiting; combination of cost/availability	20%
Don't Answer	3%

Table B.17: APS: What Does Skilled Labour Constraint Refer to?

	ITS
Mainly production line workers	33%
Mainly managerial/technical skills	21%
Combination of above	36%
Other	4%
Unanswered	6%

Table B.18: APS: What Does Uncertainty about Demand as a Limit on Future Investment Reflect?

	ITS
Weak outlook for demand across economy	28%
Weak outlook for demand in their sector	35%
Uncertain outlook for demand in the economy	32%
Uncertain outlook for demand in their sector	38%
Other	2%

The key lesson from examining the APS responses is that firms accurately interpret and complete their designated survey. This provides reassurance regarding the reliability of

Table B.19: APS: What Factors Do Firms in the SSS Consider Most Relevant for Expansion Intentions?

	SSS
Sales expectation of coming year compared to past	74%
Expectation of greater capacity in 12 months	41%
Extent of currently unused capacity	38%
Expected sales growth acceleration	52%
Other	5%

Table B.20: APS: What Do Firms in the SSS Consider when Answering Expansion Intentions?

	SSS
Extent of price discounting	36%
Severity of Competition	71%
Rising business costs in the UK	38%
Outlook to the Economy	63%
Increasing regulatory compliance	28%
Extent of unused capacity	29%
Other	3%

Table B.21: APS: What Do Firms in the DTS Assess the Adequacy of Stocks in Relation to?

	Current Month	Next Month
Current sales	26%	6%
Expected sales	16%	34%
Combination of above	34%	34%
Past levels/historical average of stock/sales ratio	6%	6%
Subjective assessment	13%	14%
Other	1%	1%

Table B.22: APS: Do ITS Firms Only Measure Current Output Solely Against Physical Capacity?

	ITS
Yes	56%
No; include utilisation of labour	40%
No; include financial resources	12%
No; include raw materials	12%
No; other	6%

the firm-level data contained in the CBI dataset.

Table B.23: APS: What do ITS Firms Measure Current Output Against?

	ITS
Level of capacity available immediately	43%
Longer term measure of capacity	52%
Other	5%

Table B.24: APS: What do ITS Firms Regard as a Satisfactory Full Rate of Operation?

	ITS
Working at full capacity	24%
Working at greater than 90%	6%
Working between 80% and 90%	49%
Working below 80%	11%
Qualitative assessment	10%

Table B.25: APS: Do ITS Firms Regard their Current Satisfactory Rate of Operation Different to Five Years Ago?

	ITS
Yes; higher	24%
Yes; lower	13%
No	62%

Table B.26: APS: Are ITS Firms Working Closer to or Further From Full Capacity than Five Years Ago?

	ITS
Closer to	40%
Further from	38%
No change	22%

Appendix C

The Uncertainty Channels

This appendix discusses the channels through which uncertainty can affect market participants - the real options channel, the credit channel and a positive channel.

C.1 The Real Options Channel

Increased uncertainty can optimally lead firms to defer investment to future periods characterised by greater levels of certainty (Cukierman, 1980; Bernanke, 1983; Bloom, 2014; Gilchrist et al., 2014). In other words, during periods of heightened uncertainty firms exhibit greater caution regarding their investment options and partake in a wait-and-see exercise before deciding to invest a sunk cost. Under these circumstances, uncertainty is operating through the real options channel. Suppose an uncertainty shock occurs in period t. The cautionary behaviour of firms (arising from the heightened uncertainty) results in a pause in investment between period's t and $t+1$, during which the firm awaits for new information on how best to proceed. The uncertainty shock has caused increased divergence between the marginal product of capital justifying investment and justifying disinvestment, creating a zone of investment inaction between t and $t+1$ while cautious firms defer investment (Bloom et al., 2007).

The option to invest is valuable due to the uncertainty regarding the future value of the investment project. In fact, a positive relationship exists between the value of the investment project and the net payoff from investing (Pindyck, 1991). If the firm were to invest in period t then it would eliminate its investment option - it has foregone the ability to wait for new information which could directly affect the desirability or timing of the project and cannot disinvest in the face of changing market conditions. The lost option value of investing is an opportunity cost (Pindyck, 1991). Note this opportunity cost (or value to waiting) would disappear if firms faced the choice of investing in period t or not at all - it is the option of deferring investing to a future period which creates this opportunity cost (Pindyck, 1991). By period $t + 1$ new information has manifested resulting in firms ending their wait-and-see behaviour - in this particular example firm's increase their investment reflecting an increase in the value of the investment project.

C.1.1 Necessary Conditions

A number of conditions need to be present for uncertainty operate through this channel. First, investment decisions need to be irreversible (Cukierman, 1980; Bernanke, 1983; Pindyck, 1991; Leahy and Whited, 1996; Bloom, 2014). To be clear, if a firm makes an irreversible investment decision in period t this means it cannot be reversed or altered in future time periods as it is a sunk cost. Examples of irreversible investment include investment in firm- or industry-specific capital, investment in capital whose purchase cost exceeds its resale value by a significant amount and investing in the training of employees who (due to government regulations) cannot be removed easily (Pindyck, 1991).

Second, firms need the ability to defer an investment decision (Bernanke, 1983; Bloom, 2014). However, it should be noted that firms need to account for the actions of both their competitors (actual and potential) and thus may not have the ability to defer investment (Pindyck, 1991). In addition, hindrances to the ability of firms to defer investment (such as costs or lack of time to defer) will mitigate against the effect of irreversibility on the investment decision (Pindyck, 1991).

Third, an information lag exists regarding returns to the irreversible investment (Cukierman, 1980; Bernanke, 1983; Pindyck, 1991; Bloom, 2014). The existence of an information lag ensures the firm lacks full information on the return to an irreversible investment with full information only being revealed in future time periods. Thus, by deferring the irreversible investment (and creating an option value for the future) the firm is awaiting better information which will signpost which option it should take. Specifically, the firm can increase its ex-ante expected utility or the expected return to an investment project by utilising resources in acquiring information on the true distribution of demand given non-prohibitive information costs (Cukierman, 1980). In other words, a large option value encourages firms to postpone irreversible investment decisions (and the resulting short-run returns) in favour of more information next period. Fourth, the firm's decision this period must influence its returns in the future (Bloom, 2014).

Furthermore, the analysis of Cukierman (1980) indicates that the real options channel of uncertainty is not dependent on the risk aversion of firms - risk neutral firms will decrease investment as a result of increased uncertainty as the revelation of new information in future periods can directly affect the firms expected profit. To be clear, because of increased uncertainty it becomes more profitable for the firm to partake in a wait-and-see exercise and make an investment decision once new information has been revealed. Cukierman (1980) demonstrates the validity of this argument through a Bayesian learning framework where a risk neutral firm (only interested in its expected return) decides whether to proceed with an investment project whose expected return depends on an unknown parameter (W) - thus making the expected return uncertain. New information is revealed to cautious firms through the realisations of a random variable (x), which depends on W, thus allowing them to make a more informed investment decision (Cukierman, 1980). In this framework, the firms maximisation problem is to choose the optimal waiting period (n^*) so as to maximise the expected return of the investment over the distribution of W (Cukierman, 1980). This n^* depends negatively on the precision of W - a decrease in the precision of W increases n^*. In other words, an increase in uncertainty (about the true value of W) increases the optimal waiting period of risk neutral firms as it becomes relatively more profitable to postpone investment and wait further information before making a decision (Cukierman, 1980).

C.1.2 When Should a Firm Invest?

Accordingly, the firm's problem is to decide whether an investment is to be undertaken (or in the case of multiple potential investments which one) and when the investment should take place. In particular, the standard investment rule indicating that net present value must exceed the cost of an investment no longer stands. By investing in this period, the firm foregoes the option to receive new information which could impact on its decision to invest and this opportunity cost needs to be explicitly accounted as a cost of investment (Bernanke, 1983; Pindyck, 1991). In particular, investment should proceed only when the value of the project exceeds the sunk (or direct) cost of investment plus the cost to reverse the investment (i.e. expected value of deferring investment) (Bernanke, 1983; Pindyck, 1991; Sarkar, 2000). For example, McDonald and Siegel (1986) argue that only when the present value of the benefits of an investment project are double the investment cost should investment proceed. In fact, under reasonable parameter values McDonald and Siegel (1986) show that investing when the net present value of investment exceeds zero can result in a reduction in the value of the project between ten and twenty percent. Accordingly, the McDonald and Siegel (1986) calibrations provide a cost justification to the wait-and-see method. This analysis confirms the earlier analysis of Cukierman (1980) who theorises that rash investment decisions could result in a lower return to the firm as a result of not waiting for new information on the state of nature to be revealed. The empirical implications of this new investment rule is that investment will only occur once the value of the investment project exceeds a critical value - this threshold depends on the parameters of the economy.

McDonald and Siegel (1986) and Pindyck (1991) examine the role of uncertainty regarding the future value of an investment project by assuming the present value of an investment project follows a geometric Brownian motion. Under this assumption the relative change in the present value is the sum of a deterministic proportional growth term and (normally distributed) random change. Furthermore, under this setup the firm will know the present value of future net cash flows by investing the sunk cost today but is unsure of what the present value would be if the sunk cost is deferred (McDonald and Siegel, 1986). Accordingly, the authors explicitly recognise that information arrives over time (via the firm observing the change in the value of the project) while ensuring the projects future value remains unknown. Only when the ratio of the present value of investment to sunk costs ($F(V)$) exceeds the critical value above which it becomes optimal to invest (V^*) does investment occur. McDonald and Siegel (1986) and Pindyck (1991) demonstrate this critical value V^* depends positively on the uncertainty parameter (σ) from the geometric Brownian motion. In other words, an increase in σ will increase $F(V)$ as well as V^* thus increasing the threshold required for investment to occur. Accordingly, increased levels of uncertainty (σ) decrease the actual investment rate of firms due to the increased critical value of investment (V^*) in spite of the increased value of the investment opportunities ($F(V)$) (McDonald and Siegel, 1986; Pindyck, 1991). The empirical implications on this are clear: increased uncertainty decreases firm investment. Pindyck (1991) further extend the analysis by letting the price of the project output follow a geometric Brownian motion (i.e. focuses on uncertainty regarding the price of the project output). Pindyck (1991) argues this is a more realistic setting and allows the ending of a project if its output price falls below variable cost. Increases in σ increase the value of the project ($V(P)$) for any P but also increase the critical price at which it is optimal to invest (P^*). The empirical implications of this literature is quite clear: irrespective of whether firms are uncertain about the future value of an investment project or output prices increases in uncertainty will have a negative effect on the firm investment decision.

C.1.3 Implications for Policymakers

A result of this channel of uncertainty is that economic agents become less responsive to business cycle conditions. In particular, stabilisation policies implemented by policy-makers becomes less effective and in order to be successful need to take into account the increased sensitivity of economic agents. In fact, it could be argued that this relates to Bernanke (1983) exposition of the bad news principle of irreversible investment - from the firms point of view only expected bad news in period $t+1$ have an impact on firms investment decisions in period t. As Bernanke (1983, p. 93) attests "a small increase in the probability of disaster cannot be offset by any potential good news in its effect on current purchases". Furthermore, this channel leads to endogenously procyclical productivity as firms of both high and low productivity restrict their expansion and contraction in productivity (respectively). Bloom et al. (2007) find evidence for this channel in a panel of UK firms from 1972 to 1991: firms facing uncertainty exhibited greater cautionary behaviour (although the authors do admit this phenomenon could arise from other factors). As Cukierman (1980) notes statements from policymakers can be contradictory and confusing - this leads firms to postpone investment as they await new information (in the form of a government decision or legislation) before deciding to invest. Therefore, the existence of this real options channel highlights the importance of policymakers ensuring their statements and pronouncements should cause the minimum disruption possible.

C.1.4 Some Dissenting Views

Not all authors argue that the real options channel posits negative relationship between investment and uncertainty. One such paper is Sarkar (2000) who analyses firm earnings uncertainty (using a geometric Brownian motion) and explicitly accounts for systematic risk (using a single-factor intertemporal Capital Asset Pricing Model). In this framework Sarkar (2000) supports the McDonald and Siegel (1986) and Pindyck (1991) argument that increases in uncertainty increase the critical value of investment. In contrast to McDonald and Siegel (1986) and Pindyck (1991), Sarkar (2000) demonstrates that the inclusion of the systematic risk component in this framework can result in an ambiguous effect of increased uncertainty on investment. Specifically, the increased uncertainty will increase firm earnings bringing them closer to the threshold crossing value (Sarkar, 2000). Thus, in this setup both firm earnings and its corresponding critical value have increased as a result of increased uncertainty. The probability of a firm investing is positively related to the level of uncertainty - but only when the level of uncertainty is already low. Thus, an increase in uncertainty will increase investment in a low uncertainty environment. For already high levels of uncertainty, an increase in uncertainty will decrease the actual investment of the firm.

The conclusions in Sarkar (2000) are broadly replicated in Wong (2007) who instead considers the effect of uncertainty on investment timing. Wong (2007) also details a non-monotonic relationship between the critical investment level and uncertainty driven by two countervailing forces: a risk factor (increased uncertainty increases the investment threshold by making waiting more desirable) and return factor (increased uncertainty makes waiting more costly lowering the investment threshold). The non-monotonicity of the relationship arises due to the domination of the risk factor for high levels of uncertainty and the return factor for low levels of uncertainty (Wong, 2007). In addition, Wong (2007) asserts that a positive relationship between investment and uncertainty is more likely to occur for high growth projects and for relatively less risky projects increased uncertainty can reduce the time to invest (thus increasing investment as the return factor dominates for these less risky projects).

C.2 The Credit Channel

As a result of financial market frictions uncertainty operating through the credit (or risk premium) channel impacts negatively on the level of investment by raising the cost of finance (Bloom, 2014; Gilchrist et al., 2014; Popp and Zhang, 2016). In particular, the credit channel consist of two components - debt finance and equity finance. In the first case, the perceived riskiness of a firm is heightened by increased uncertainty resulting in lenders (in turn facing greater expected losses from potential default) either raising the cost of finance or limiting the availability of finance (Bloom et al., 2014; Popp and Zhang, 2016). Specifically, as uncertainty increases the probability of default for a firm increases which in turn may contract or stop investment with the aim of improving their financial position (Popp and Zhang, 2016). Furthermore, borrowing finance may have become more difficult as the cost and difficult of borrowing have increased due to the higher expected loss for lenders arising from the perceived riskiness of firms (Popp and Zhang, 2016).

In the equity finance case, higher uncertainty exacerbates information asymmetry in financial markets leading to an increase in the credit spread as investors require greater compensation for investment in risky assets (Gilchrist et al., 2014). Specifically, the increased uncertainty leads investors to demand a greater liquidity premium and greater compensation for holding the firm's bonds in particular since with the increased uncertainty problems of adverse selection and selecting firms of good quality (or creditworthiness) have now been amplified (Popp and Zhang, 2016). The result is it becomes more difficult and more costly for firms to raise finance on the equity markets (Popp and Zhang, 2016).

Existing literature highlights the recent events of the financial crisis a evidence for the existence and importance of this uncertainty channel. For example Arellano et al. (2016) highlight that during the financial crisis the credit spread of firms increased while debt purchases and equity payouts decreased. In addition, Popp and Zhang (2016) assert that the credit channel undertakes a heightened importance during recessions - from the debt component lenders become more unwilling to lend and businesses more likely to contract their real activities (perhaps motivated by harder to achieve credit) while from the equity component greater pessimism, a desire for a flight to quality firms and increased financial restrictions on lenders themselves

C.3 Positive Channels

The preceding arguments have hypothesised that increases in uncertainty decrease investment. This has been predicated on the fact that marginal revenue product of capital is concave (Leahy and Whited, 1996). In the case where the marginal revenue product of capital is convex then an increase in uncertainty leads to an increase in investment (i.e. a positive relationship between uncertainty and investment) (Leahy and Whited, 1996; Bloom, 2014). Leahy and Whited (1996) find no evidence to support the existence of a positive relationship between investment and uncertainty.

Another positive channel is the Oi-Hartman-Abel channel whereby firms expand and contract in the face of positive and negative shocks (respectively) so that a mean preserving spreads in outcomes can increase average output (Bloom, 2014). Specifically, uncertainty will increase expected profits if these profits are convex in demand or costs (Bloom, 2014). This channel requires firms can easily expand or contract leading Bloom (2014) to argue this channel is more effective in the medium- to long-term.

Appendix D

Referenced (but Unused) Quantification Measures from Chapter 3

For completeness this appendix presents expected output growth (generated from the Anderson-Pesaran regression approach) and output uncertainty (from the square of the industry-level expectation error (Equation 3.10)) - both of which were mentioned in Chapter 3 but not used.

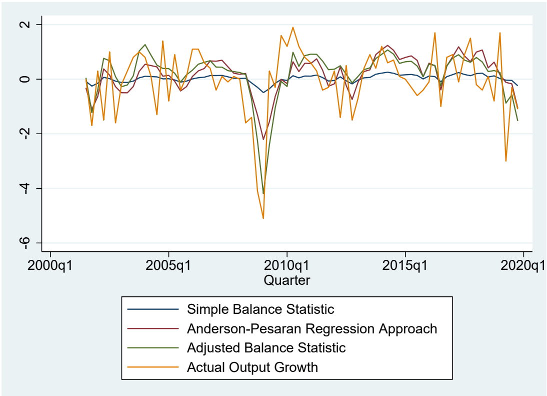
D.1 Expected Output Growth using the Anderson-Pesaran Regression Approach

Figure D.1a to Figure D.1c plots the series generated by Equation 3.2, Equation 3.7, the expected output growth series generated by the Anderson-Pesaran regression approach[1] alongside actual industry-level output growth. The Anderson-Pesaran regression approach expected output growth series has a correlation of 0.51, 0.43 and 0.58 with actual output growth for the manufacturing and mining, service and distributive trades sectors (respectively). These correlations are very similar to the correlation between the simple balance statistic and actual output growth - and are less than the correlation between the adjusted balance statistic and actual output growth. In addition, while the range of the Anderson-

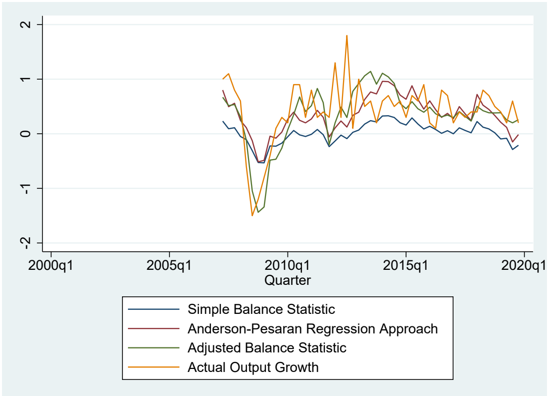
[1] The Anderson-Pesaran regression approach is the same as Equation 3.2 except with $+\alpha_j$ and $-\beta_j$ instead of +1 and -1 (respectively). An estimate of α_j and β_j is obtained from regressing $y_{j,t}$ (industry-level actual output growth obtained from official statistics) on ${}_{t+1}U_{j,t}$ and ${}_{t+1}D_{j,t}$ (i.e. the proportion of firms in industrial sector j in period $t+1$ who reported their actual output did go "up" or "down" in period t, respectively).

Pesaran regression approach expected output growth series is greater than the range of the simple balance statistic, it is smaller than the range of the adjusted balance statistic. Finally, the relatively large standard errors of the coefficient estimates reflects some considerable residual variability - indicating the benefits of taking into account possible time-variation in the parameters.

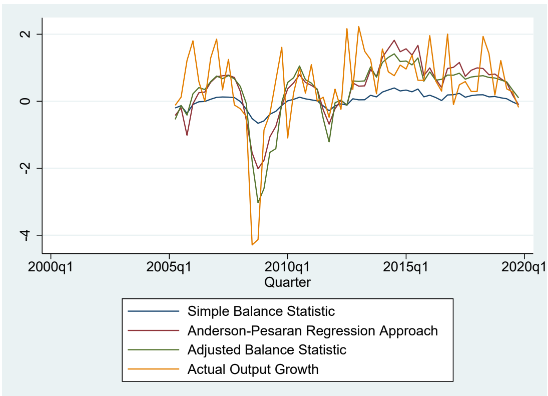
Figure D.1: The Anderson-Pesaran Regression Approach Expected Output Growth Series Compared to the Simple Balance Statistic, the Adjusted Balance Statistic and Actual Output Growth



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

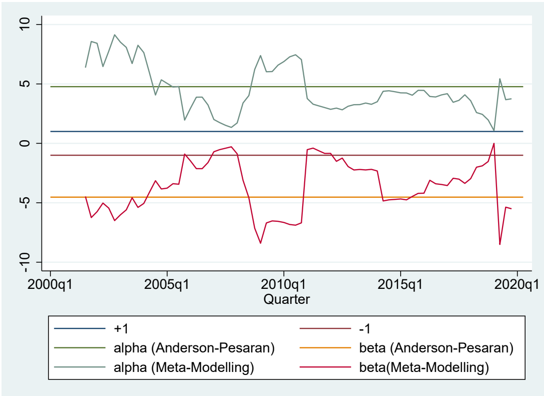
Note: The simple balance statistic, at the beginning of period t, is defined for each industrial sector j as ${}_ty^e_{R,j,t} = {}_tU^e_{j,t} - {}_tD^e_{j,t}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t, respectively. The Anderson-Pesaran regression approach is the same as Equation 3.2 except with $+\alpha_j$ and $-\beta_j$ instead of +1 and -1 (respectively). An estimate of α_j and β_j is obtained from regressing $y_{j,t}$ (industry-level actual output growth obtained from official statistics) on ${}_{t+1}U_{j,t}$ and ${}_{t+1}D_{j,t}$ (i.e. the proportion of firms in industrial sector j in period $t+1$ who reported their actual output did go "up" or "down" in period t, respectively). The adjusted balance statistic, at the beginning of period t, is defined for each industrial sector j as ${}_ty^e_{A,j,t} = (\alpha_{meta,j,t}){}_tU^e_{j,t} - (\beta_{meta,j,t}){}_tD^e_{j,t}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively), $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

The quantification of survey responses "up" and "down" is plotted in Figure D.2a to Figure D.2c for each quantification strategy (i.e. the balance statistic, the Anderson-Pesaran regression approach and the meta-modelling quantification approach). Recall the balance statistic quantifies "up" as +1 while "down" is quantified as -1. Note that in the Anderson-Pesaran regression approach $+\alpha_j$ and $-\beta_j$ are constant over time. Specifically, the coefficient estimates (standard errors) are $\alpha_j = 4.77$ (0.85) and $\beta_j = 4.53$ (0.75) for the manufacturing and mining sector, $\alpha_j = 2.58$ (0.40) and $\beta_j = 1.07$ (0.34) for the service sector and $\alpha_j = 4.26$ (0.54) and $\beta_j = 3.18$ (0.55) for the distributive trades sector. The coefficient estimates for manufacturing and mining firms are broadly consistent with the symmetric quantification assumption of the simple balance statistic - although this is not replicated for service or distributive trades firms. Only the meta-modelling quantification approach allows for time-varying quantification of the survey responses "up" and "down".

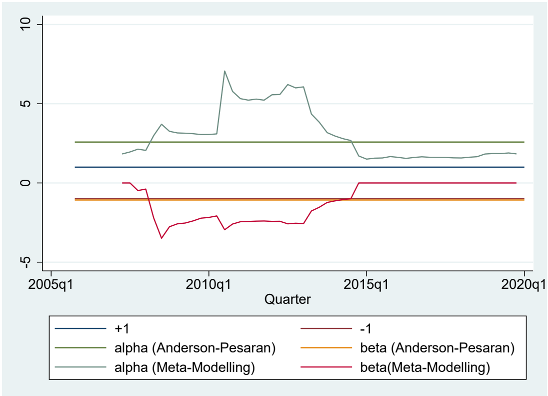
D.2 Output Uncertainty using the Square of the Industry-Level Expectation Error

Squaring Equation 3.10 yields a measure of output uncertainty for period t - depicted in Figure D.3a to Figure D.3c. However, this is an ex-post measure of uncertainty as it involves the actual outcome which is unknown at the time expectations are formed. Thus, it does not properly capture the uncertainty surrounding the reported expectation at the time it was reported. In addition, this output uncertainty measure is procyclical for the service sector (with a correlation of 0.37 between industry-level output uncertainty and actual output growth). It is countercyclical, though, for the manufacturing and mining and distributive trades sectors with correlations -0.35 and -0.16 (respectively).

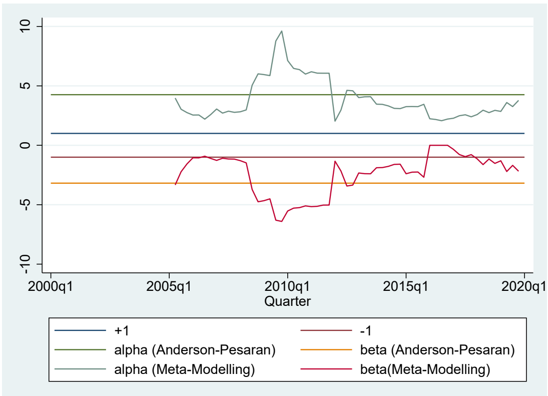
Figure D.2: The Quantification of Survey Responses “Up” and “Down” for each Quantification Strategy



(a) Manufacturing and Mining Sector Firms



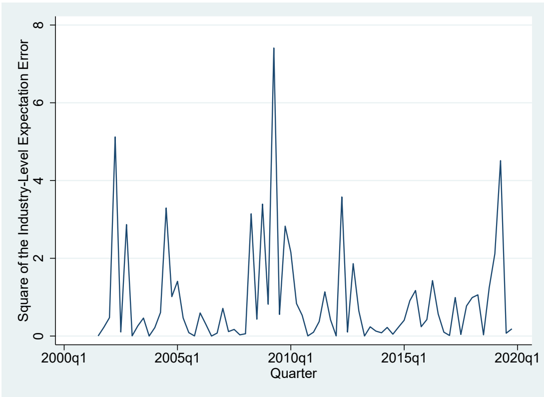
(b) Service Sector Firms



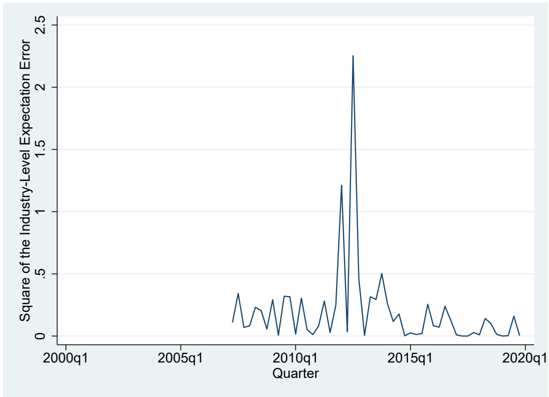
(c) Distributive Trades Sector Firms

Note: The simple balance statistic, at the beginning of period t, is defined for each industrial sector j as ${}_ty^e_{R,j,t} = {}_tU^e_{j,t} - {}_tD^e_{j,t}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t, respectively. The Anderson-Pesaran regression approach is the same as Equation 3.2 except with $+\alpha_j$ and $-\beta_j$ instead of +1 and -1 (respectively). An estimate of α_j and β_j is obtained from regressing $y_{j,t}$ (industry-level actual output growth obtained from official statistics) on ${}_{t+1}U_{j,t}$ and ${}_{t+1}D_{j,t}$ (i.e. the proportion of firms in industrial sector j in period $t+1$ who reported their actual output did go “up” or “down” in period t, respectively). The adjusted balance statistic, at the beginning of period t, is defined for each industrial sector j as ${}_ty^e_{A,j,t} = (\alpha_{meta,j,t})_tU^e_{j,t} - (\beta_{meta,j,t})_tD^e_{j,t}$ where ${}_tU^e_{j,t}$ and ${}_tD^e_{j,t}$ are the proportion of firms at the beginning of period t who expect output growth to go up or go down in period t (respectively), $\alpha_{meta,j,t}$ is the average percentage increase in output for firms experiencing a rise in their output and $\beta_{meta,j,t}$ is the average percentage decrease in output for firms experiencing a fall in their output. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

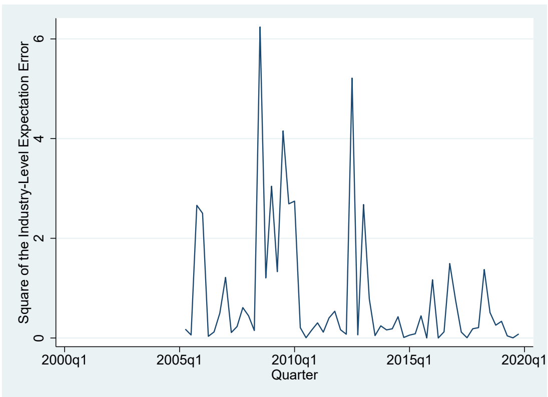
Figure D.3: Output Uncertainty using the Square of the Industry-Level Expectation Error



(a) Manufacturing and Mining Sector Firms



(b) Service Sector Firms



(c) Distributive Trades Sector Firms

Note: The squared quantitative meta-model expectation error, at the beginning of period t, is defined for each industrial sector j as $(\epsilon\epsilon_{j,t})^2 = ({}_t y^e_{A,j,t} - y_{j,t})^2$ where ${}_t y^e_{A,j,t}$ is expected output growth as defined by the meta-model adjusted balance statistic and $y_{j,t}$ is actual output growth. Firm-level survey data is sourced from the Confederation of British Industry (CBI) Industrial Trends Survey (ITS), Service Sector Survey (SSS) and Distributive Trades Survey (DTS) for manufacturing and mining firms, service sector firms and distributive trades sector firms (respectively). Data for actual output growth is sourced from the Office for National Statistics (ONS) L3BN, L3E2, and L2NE series for the manufacturing and mining, service and distributive trades sectors respectively. CBI data is available from 2000Q1, 2005Q4 and 2003Q4 until 2020Q1 for the manufacturing and mining, service and distributive trades sectors (respectively). ONS data is available for each industrial sector j until 2019Q4.

Appendix E

Chapter 4 Appendix

E.1 Tables of Results

Table E.1: Econometric Results of Equation 4.28

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE
Capacity, $\Delta\Omega_{j,t}$									
Lagged Capacity Utilisation Growth, $\Delta\Omega_{j,t-1}$	-0.030	-0.030	-0.029	-0.031	-0.029	-0.032	-0.028	-0.031	-0.028
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Capital Error Correction, $k_{j,t-1} - y_{j,t-1}$	-2.637	-2.761	-2.674	-2.452	-2.639	-2.677	-2.695	-2.717	-2.936
	(3.70)	(3.71)	(3.76)	(3.69)	(3.75)	(3.67)	(3.77)	(3.70)	(3.92)
Capacity Error Correction, $\Omega_{j,t-1} - \Omega^*_{j,t-1}$	-0.711***	-0.707***	-0.715***	-0.709***	-0.707***	-0.706***	-0.715***	-0.710***	-0.708***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Cash-Flow, $\frac{c_{j,t}}{K_{j,t-1}}$	-98.489	-86.290	-96.608	-95.610	-96.732	-98.877	-100.945	-99.489	-85.125
	(145.09)	(146.47)	(143.57)	(143.14)	(143.02)	(146.24)	(145.96)	(145.16)	(144.82)
Lag Cash-Flow, $\frac{c_{j,t-1}}{K_{j,t-2}}$	-89.564	-98.774	-90.627	-88.240	-92.963	-91.172	-90.480	-89.788	-106.819
	(72.88)	(74.53)	(73.21)	(73.23)	(71.86)	(74.78)	(73.31)	(73.03)	(75.97)
Sales Growth, $\Delta y_{j,t}$	50.464***	50.063***	50.336***	50.720***	50.624***	50.589***	50.710***	50.756***	50.409***
	(11.50)	(11.55)	(11.82)	(11.60)	(11.73)	(11.65)	(11.75)	(11.50)	(12.23)
Sales Growth Square, $(\Delta y_{j,t})^2$	-37.746	-34.415	-39.245	-38.959	-34.987	-38.299	-39.535	-38.010	-37.168
	(43.88)	(43.43)	(45.54)	(44.53)	(43.49)	(44.34)	(44.97)	(43.61)	(46.31)
Inadequate Net Return, $_{t-1}poor_{j,t}$		-0.879							-0.944
		(1.22)							(1.20)
Shortage of Internal Finance, $_{t-1}internal_{j,t}$			-1.422						-1.510
			(1.80)						(1.76)
Inability to Raise External Finance, $_{t-1}external_{j,t}$				-0.833					-0.350
				(2.00)					(1.84)
Cost of Finance, $_{t-1}cost_{j,t}$					-6.625				-6.803
					(5.04)				(4.98)
Uncertainty about Demand, $_{t-1}uncertainty_{j,t}$						0.273			0.137
						(0.81)			(0.83)
Shortage of Labour, $_{t-1}labour_{j,t}$							-0.357		-0.845
							(2.22)		(2.19)
Other, $_{t-1}other_{j,t}$								-0.925	-1.068
								(3.61)	(3.37)
Constant	52.347***	52.076***	52.571***	52.248***	51.959***	51.905***	52.710***	52.135***	52.400***
	(8.63)	(8.66)	(8.69)	(8.58)	(8.84)	(8.55)	(8.51)	(8.84)	(8.91)
Observations	1159	1159	1159	1159	1159	1159	1159	1159	1159
Firms	328	328	328	328	328	328	328	328	328
m1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
m2	0.92	0.95	0.90	0.93	0.89	0.90	0.92	0.92	0.90
Hansen	0.41	0.40	0.36	0.40	0.32	0.45	0.40	0.41	0.33

Table reports coefficient estimates and robust standard errors (in brackets). Model estimator is the Arellano and Bover (1995) and Blundell and Bond (1998) system GMM. Following Bloom et al. (2007) the set of instruments for the first-difference equation are the second and third lags of the endogenous variables and the set of instruments for the level equation is the first lag of the endogenous variables. The set of endogenous variables are all the quantitative FAME variables. Year dummies excluded from table of results. Validity of the instruments is tested using the Hansen test of overidentifying restrictions while the Lagrange multiplier tests for serial correlation in the error term. The Arellano-Bond test for autocorrelation rejects second-order serial correlation (and above) in the first-differenced residuals while the Hansen test does not reject the validity of overidentifying restrictions. Column one presents the baseline estimation, columns two to eight individually add investment constraints to the baseline specification and column nine includes all investment constraints with the baseline model. *p<0.1 **p<0.05 ***p<0.01

Table E.2: Econometric Estimates of Equation 4.9

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Investment Rate, $\Delta k_{j,t}$	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE
Lagged Investment Rate, $\Delta k_{j,t-1}$	0.105*	0.106*	0.105*	0.106*	0.105*	0.103*	0.104*	0.105*	0.099*
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Sales Growth, $\Delta y_{j,t}$	0.381***	0.373***	0.378***	0.370***	0.370***	0.348**	0.371***	0.373***	0.350**
	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Capital Error Correction, $k_{j,t-1} - y_{j,t-1}$	-0.115**	-0.127***	-0.122***	-0.127***	-0.124***	-0.125***	-0.122***	-0.125***	-0.122***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Cash-Flow, $\frac{c_{j,t}}{K_{j,t-1}}$	2.089***	1.776**	1.995***	1.936**	1.969***	1.923**	1.987***	1.963**	1.770**
	(0.81)	(0.75)	(0.75)	(0.78)	(0.76)	(0.78)	(0.76)	(0.77)	(0.75)
Lag Cash-Flow, $\frac{c_{j,t-1}}{K_{j,t-2}}$	-2.498***	-2.509***	-2.578***	-2.618***	-2.604***	-2.506***	-2.570***	-2.610***	-2.292***
	(0.68)	(0.71)	(0.71)	(0.71)	(0.71)	(0.75)	(0.71)	(0.71)	(0.74)
Sales Growth Square, $(\Delta y_{j,t})^2$	-0.039	-0.069	-0.102	-0.091	-0.085	-0.133	-0.085	-0.111	-0.060
	(0.91)	(1.16)	(1.21)	(1.16)	(1.13)	(1.16)	(1.13)	(1.16)	(1.15)
Inadequate Net Return, ${}_{t-1}poor_{j,t}$		0.012**							0.013**
		(0.01)							(0.01)
Shortage of Internal Finance, ${}_{t-1}internal_{j,t}$			0.005						0.001
			(0.01)						(0.01)
Inability to Raise External Finance, ${}_{t-1}external_{j,t}$				-0.004					-0.005
				(0.01)					(0.02)
Cost of Finance, ${}_{t-1}cost_{j,t}$					-0.010				-0.012
					(0.03)				(0.03)
Uncertainty about Demand, ${}_{t-1}uncertainty_{j,t}$						-0.009*			-0.011**
						(0.01)			(0.01)
Shortage of Labour, ${}_{t-1}labour_{j,t}$							-0.008		-0.008
							(0.01)		(0.01)
Other, ${}_{t-1}other_{j,t}$								0.005	0.010
								(0.02)	(0.02)
Constant	-0.070**	-0.087***	-0.082**	-0.083**	-0.082**	-0.077**	-0.080**	-0.082**	-0.080**
	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Observations	2110	1556	1556	1556	1556	1556	1556	1556	1556
Firms	652	444	444	444	444	444	444	444	444
m1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
m2	0.79	0.88	0.88	0.88	0.88	0.90	0.88	0.89	0.90
Hansen	0.66	0.49	0.27	0.48	0.51	0.56	0.48	0.50	0.31

Table reports coefficient estimates and robust standard errors (in brackets). Model estimator is the Arellano and Bover (1995) and Blundell and Bond (1998) system GMM. Following Bloom et al. (2007) the set of instruments for the first-difference equation are the second and third lags of the endogenous variables and the set of instruments for the level equation is the first lag of the endogenous variables. The set of endogenous variables are all the quantitative FAME variables. Year dummies excluded from table of results. Validity of the instruments is tested using the Hansen test of overidentifying restrictions while the Lagrange multiplier tests for serial correlation in the error term. The Arellano-Bond test for autocorrelation rejects second-order serial correlation (and above) in the first-differenced residuals while the Hansen test does not reject the validity of overidentifying restrictions. Column one presents the baseline estimation, columns two to eight individually add investment constraints to the baseline specification and column nine includes all investment constraints with the baseline model. *p<0.1 **p<0.05 ***p<0.01

Table E.3: Econometric Estimates of Equation 4.9 with Convex Adjustment Costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Investment Rate, $\Delta k_{j,t}$	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE
Lagged Investment Rate, $\Delta k_{j,t-1}$	0.111*	0.096	0.094	0.095	0.095	0.092	0.094	0.095	0.086
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)
Convex Adjustment Cost, $(\Delta k_{j,t-1})^2$	-0.016	0.025	0.029	0.029	0.026	0.033	0.029	0.028	0.039
	(0.15)	(0.15)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)
Sales Growth, $\Delta y_{j,t}$	0.380***	0.374***	0.378***	0.370***	0.371***	0.351**	0.372***	0.373***	0.350**
	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Capital Error Correction, $k_{j,t-1} - y_{j,t-1}$	-0.116**	-0.126***	-0.121**	-0.125**	-0.123**	-0.123**	-0.120**	-0.124**	-0.120**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Cash-Flow, $\frac{c_{j,t}}{K_{j,t-1}}$	2.098***	1.762**	1.979***	1.916**	1.951***	1.905**	1.970***	1.946**	1.747**
	(0.78)	(0.74)	(0.73)	(0.77)	(0.75)	(0.77)	(0.75)	(0.75)	(0.74)
Lag Cash-Flow, $\frac{c_{j,t-1}}{K_{j,t-2}}$	-2.520***	-2.480***	-2.541***	-2.582***	-2.571***	-2.465***	-2.534***	-2.574***	-2.247***
	(0.71)	(0.74)	(0.75)	(0.75)	(0.75)	(0.78)	(0.74)	(0.75)	(0.78)
Sales Growth Square, $(\Delta y_{j,t})^2$	-0.034	-0.057	-0.088	-0.080	-0.077	-0.128	-0.076	-0.101	-0.031
	(0.93)	(1.16)	(1.21)	(1.16)	(1.13)	(1.14)	(1.12)	(1.15)	(1.14)
Inadequate Net Return, ${}_{t-1}poor_{j,t}$		0.012**							0.012**
		(0.01)							(0.01)
Shortage of Internal Finance, ${}_{t-1}internal_{j,t}$			0.004						0.001
			(0.01)						(0.01)
Inability to Raise External Finance, ${}_{t-1}external_{j,t}$				-0.004					-0.005
				(0.01)					(0.02)
Cost of Finance, ${}_{t-1}cost_{j,t}$					-0.010				-0.011
					(0.03)				(0.03)
Uncertainty about Demand, ${}_{t-1}uncertainty_{j,t}$						-0.009*			-0.011**
						(0.01)			(0.01)
Shortage of Labour, ${}_{t-1}labour_{j,t}$							-0.008		-0.008
							(0.01)		(0.01)
Other, ${}_{t-1}other_{j,t}$								0.005	0.010
								(0.02)	(0.02)
Constant	-0.071*	-0.086**	-0.081**	-0.082**	-0.081**	-0.076**	-0.079**	-0.081**	-0.078**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
Observations	2110	1556	1556	1556	1556	1556	1556	1556	1556
Firms	652	444	444	444	444	444	444	444	444
m1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
m2	0.80	0.84	0.84	0.85	0.85	0.87	0.85	0.85	0.85
Hansen	0.64	0.47	0.26	0.46	0.49	0.54	0.46	0.49	0.30

Table reports coefficient estimates and robust standard errors (in brackets). Model estimator is the Arellano and Bover (1995) and Blundell and Bond (1998) system GMM. Following Bloom et al. (2007) the set of instruments for the first-difference equation are the second and third lags of the endogenous variables and the set of instruments for the level equation is the first lag of the endogenous variables. The set of endogenous variables are all the quantitative FAME variables. Year dummies excluded from table of results. Validity of the instruments is tested using the Hansen test of overidentifying restrictions while the Lagrange multiplier tests for serial correlation in the error term. The Arellano-Bond test for autocorrelation rejects second-order serial correlation (and above) in the first-differenced residuals while the Hansen test does not reject the validity of overidentifying restrictions. Column one presents the baseline estimation, columns two to eight individually add investment constraints to the baseline specification and column nine includes all investment constraints with the baseline model. *p<0.1 **p<0.05 ***p<0.01

Table E.4: Econometric Results of Equation 4.25

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Investment Rate, $\Delta k_{j,t}$	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE
Lagged Investment Rate, $\Delta k_{j,t-1}$	0.142**	0.141**	0.144**	0.142**	0.142**	0.138**	0.143**	0.143**	0.138**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Capital Error Correction, $k_{j,t-1} - y_{j,t-1}$	-0.064*	-0.068**	-0.064*	-0.064*	-0.066*	-0.062*	-0.067*	-0.065*	-0.067*
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
Capacity Error Correction, $\Omega_{j,t-1} - \Omega^*_{j,t-1}$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.003***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cash-Flow, $\frac{c_{j,t}}{K_{j,t-1}}$	3.862***	3.613***	3.873***	3.866***	3.860***	3.788***	3.828***	3.860***	3.543***
	(1.21)	(1.21)	(1.20)	(1.21)	(1.22)	(1.21)	(1.20)	(1.21)	(1.22)
Lag Cash-Flow, $\frac{c_{j,t-1}}{K_{j,t-2}}$	-2.550***	-2.443***	-2.545***	-2.552***	-2.573***	-2.405***	-2.565***	-2.549***	-2.299***
	(0.61)	(0.59)	(0.60)	(0.60)	(0.61)	(0.63)	(0.60)	(0.61)	(0.62)
Inadequate Net Return, ${}_{t-1}poor_{j,t}$		0.014**							0.014**
		(0.01)							(0.01)
Shortage of Internal Finance, ${}_{t-1}internal_{j,t}$			0.008						0.006
			(0.02)						(0.02)
Inability to Raise External Finance, ${}_{t-1}external_{j,t}$				0.001					-0.003
				(0.01)					(0.01)
Cost of Finance, ${}_{t-1}cost_{j,t}$					-0.021				-0.013
					(0.03)				(0.02)
Uncertainty about Demand, ${}_{t-1}uncertainty_{j,t}$						-0.010*			-0.011**
						(0.01)			(0.01)
Shortage of Labour, ${}_{t-1}labour_{j,t}$							-0.016		-0.012
							(0.01)		(0.01)
Other, ${}_{t-1}other_{j,t}$								0.003	0.006
								(0.02)	(0.01)
Constant	-0.227***	-0.230***	-0.223***	-0.227***	-0.229***	-0.213***	-0.232***	-0.226***	-0.215***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
Observations	1446	1446	1446	1446	1446	1446	1446	1446	1446
Firms	428	428	428	428	428	428	428	428	428
m1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
m2	1.00	0.98	0.99	1.00	0.99	0.99	1.00	1.00	1.00
Hansen	0.37	0.50	0.37	0.37	0.39	0.39	0.44	0.37	0.52

Table reports coefficient estimates and robust standard errors (in brackets). Model estimator is the Arellano and Bover (1995) and Blundell and Bond (1998) system GMM. Following Bloom et al. (2007) the set of instruments for the first-difference equation are the second and third lags of the endogenous variables and the set of instruments for the level equation is the first lag of the endogenous variables. The set of endogenous variables are all the quantitative FAME variables. Year dummies excluded from table of results. Validity of the instruments is tested using the Hansen test of overidentifying restrictions while the Lagrange multiplier tests for serial correlation in the error term. The Arellano-Bond test for autocorrelation rejects second-order serial correlation (and above) in the first-differenced residuals while the Hansen test does not reject the validity of overidentifying restrictions. Column one presents the baseline estimation, columns two to eight individually add investment constraints to the baseline specification and column nine includes all investment constraints with the baseline model. *p<0.1 **p<0.05 ***p<0.01

Table E.5: Econometric Results of Equation 4.25 with Sales Growth

Investment Rate, $\Delta k_{j,t}$	(1) Coeff./SE	(2) Coeff./SE	(3) Coeff./SE	(4) Coeff./SE	(5) Coeff./SE	(6) Coeff./SE	(7) Coeff./SE	(8) Coeff./SE	(9) Coeff./SE
Lagged Investment Rate, $\Delta k_{j,t-1}$	0.115**	0.114**	0.115**	0.114**	0.115**	0.110*	0.112*	0.115**	0.109*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Capital Error Correction, $k_{j,t-1} - y_{j,t-1}$	-0.065*	-0.068*	-0.063*	-0.067*	-0.065*	-0.065*	-0.063*	-0.065*	-0.068*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Capacity Error Correction, $\Omega_{j,t-1} - \Omega^*_{j,t-1}$	0.002***	0.002***	0.002**	0.002***	0.002***	0.002**	0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cash-Flow, $\frac{c_{j,t}}{K_{j,t-1}}$	3.414***	3.181***	3.438***	3.399***	3.416***	3.349***	3.412***	3.413***	3.105***
	(1.11)	(1.14)	(1.11)	(1.12)	(1.11)	(1.11)	(1.11)	(1.11)	(1.13)
Lag Cash-Flow, $\frac{c_{j,t-1}}{K_{j,t-2}}$	-2.466***	-2.336***	-2.447***	-2.481***	-2.465***	-2.368***	-2.443***	-2.462***	-2.239***
	(0.65)	(0.64)	(0.64)	(0.65)	(0.65)	(0.65)	(0.65)	(0.65)	(0.65)
Sales Growth, $\Delta y_{j,t}$	0.395***	0.393***	0.398***	0.393***	0.395***	0.390***	0.400***	0.393***	0.398***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Sales Growth Square, $(\Delta y_{j,t})^2$	-0.799	-0.813	-0.841	-0.774	-0.804	-0.794	-0.826	-0.795	-0.810
	(0.95)	(0.96)	(0.94)	(0.94)	(0.95)	(0.93)	(0.91)	(0.95)	(0.88)
Inadequate Net Return, ${}_{t-1}poor_{j,t}$		0.015**							0.015**
		(0.01)							(0.01)
Shortage of Internal Finance, ${}_{t-1}internal_{j,t}$			0.008						0.008
			(0.02)						(0.02)
Inability to Raise External Finance, ${}_{t-1}external_{j,t}$				-0.004					-0.007
				(0.01)					(0.01)
Cost of Finance, ${}_{t-1}cost_{j,t}$					-0.004				-0.008
					(0.03)				(0.03)
Uncertainty about Demand, ${}_{t-1}uncertainty_{j,t}$						-0.007			-0.007
						(0.01)			(0.01)
Shortage of Labour, ${}_{t-1}labour_{j,t}$							-0.021		-0.021
							(0.01)		(0.01)
Other, ${}_{t-1}other_{j,t}$								0.001	0.008
								(0.02)	(0.02)
Constant	-0.223***	-0.235***	-0.220***	-0.226***	-0.223***	-0.214***	-0.227***	-0.222***	-0.223***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Observations	1425	1425	1425	1425	1425	1425	1425	1425	1425
Firms	416	416	416	416	416	416	416	416	416
m1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
m2	0.99	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.97
Hansen	0.30	0.42	0.35	0.30	0.30	0.31	0.31	0.30	0.47

Table reports coefficient estimates and robust standard errors (in brackets). Model estimator is the Arellano and Bover (1995) and Blundell and Bond (1998) system GMM. Following Bloom et al. (2007) the set of instruments for the first-difference equation are the second and third lags of the endogenous variables and the set of instruments for the level equation is the first lag of the endogenous variables. The set of endogenous variables are all the quantitative FAME variables. Year dummies excluded from table of results. Validity of the instruments is tested using the Hansen test of overidentifying restrictions while the Lagrange multiplier tests for serial correlation in the error term. The Arellano-Bond test for autocorrelation rejects second-order serial correlation (and above) in the first-differenced residuals while the Hansen test does not reject the validity of overidentifying restrictions. Column one presents the baseline estimation, columns two to eight individually add investment constraints to the baseline specification and column nine includes all investment constraints with the baseline model. *p<0.1 **p<0.05 ***p<0.01

E.2 Some Algebra

To make solving the firm maximisation problem easier, transform the Lagrangian by adding and subtracting $p_t^K K_t$ and $p_t^L L_t$ to the right-hand side of Equation 4.17:

$$\begin{aligned}\mathfrak{L}_{j,t} = \sum_{t=0}^{\infty} \beta^t \Big(& p_{j,t} A_{j,t} K_{j,t}^{\alpha} (\Omega_{j,t} L_{j,t})^{1-\alpha} - \left(\frac{w_{j,t}}{2}\Omega_{j,t}\right)(\Omega_{j,t}) L_{j,t} \\ & - \frac{\gamma}{2}\left(\frac{I_{j,t}^K}{K_{j,t}}\right)^2 I_{j,t}^K - \frac{\varepsilon}{2}\left(\frac{I_{j,t}^L}{\Omega_{j,t} L_{j,t}}\right)^2 I_{j,t}^L \\ & + p_{j,t}^K (I_{j,t}^K + (1-\delta)K_{j,t} - K_{j,t}) - p_{j,t}^K (K_{j,t+1} - K_{j,t}) \\ & + p_{j,t}^L (I_{j,t}^L + (1-\mu)\Omega_{j,t} L_{j,t} - \Omega_{j,t} L_{j,t}) - p_{j,t}^L (\Omega_{j,t+1} L_{j,t+1} - \Omega_{j,t} L_{j,t}) \Big)\end{aligned} \tag{E.1}$$

For ease of notation let

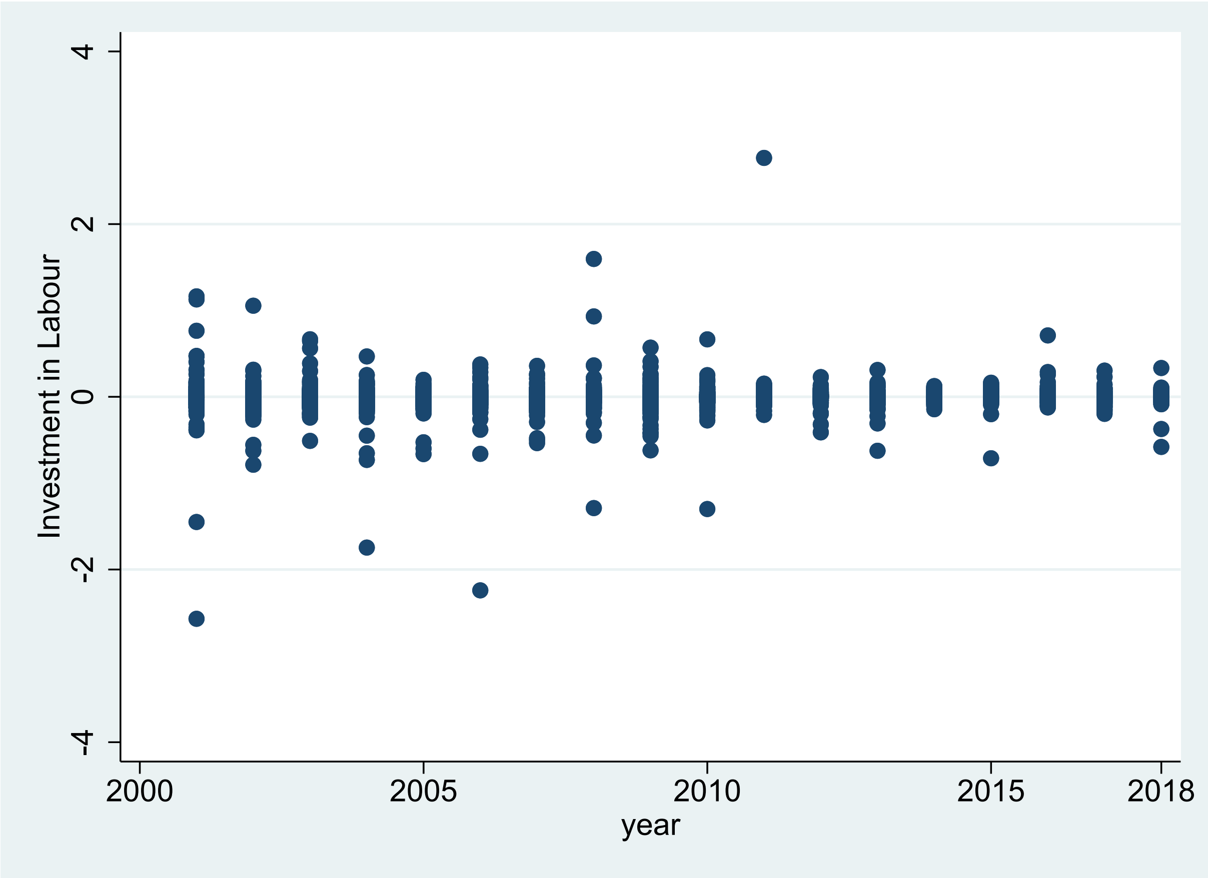
$$\begin{aligned}H_{j,t} = & p_{j,t} A_{j,t} K_{j,t}^{\alpha} (\Omega_{j,t} L_{j,t})^{1-\alpha} - \left(\frac{w_{j,t}}{2}\Omega_{j,t}\right)(\Omega_{j,t}) L_{j,t} \\ & - \frac{\gamma}{2}\left(\frac{I_{j,t}^K}{K_{j,t}}\right)^2 I_{j,t}^K - \frac{\varepsilon}{2}\left(\frac{I_{j,t}^L}{\Omega_{j,t} L_{j,t}}\right)^2 I_{j,t}^L \\ & + p_{j,t}^K (I_{j,t}^K + (1-\delta)K_{j,t} - K_{j,t}) + p_{j,t}^L (I_{j,t}^L + (1-\mu)\Omega_{j,t} L_{j,t} - \Omega_{j,t} L_{j,t})\end{aligned} \tag{E.2}$$

The short-run equilibrium defined by Equation 4.18, Equation 4.19 and Equation 4.20 is obtained by differentiating Equation E.2 with respect to $\Omega_{j,t}$, $I_{j,t}^K$ and $I_{j,t}^L$ (respectively). The intertemporal equations defined by Equation 4.21 and Equation 4.22 are obtained from $p_t^K - p_{t-1}^K - r p_t^K = -\frac{\partial H_{j,t}}{\partial K_{j,t}}$ and $p_t^L - p_{t-1}^L - r p_t^L = -\frac{\partial H_{j,t}}{\partial L_{j,t}}$ (respectively). Note that since $\frac{I_{j,t}^L}{L_{j,t}} \approx 0$, it is dropped from Equation 4.22. Specifically, it has a mean value of -0.003 over the course of the sample and Figure E.1 and Figure E.2 show the scatter plot of $\frac{I_{j,t}^L}{L_{j,t}}$ and the yearly average of $\frac{I_{j,t}^L}{L_{j,t}}$ over the course of the sample. As both figures indicate, $\frac{I_{j,t}^L}{L_{j,t}} \approx 0$ is negligible and thus is dropped from Equation 4.22.

To calculate the steady-state for the capital stock set Equation 4.21 equal to zero and note that "constant growth rate of capital [implies] p^K is constant, since the growth rate of capital is a function solely of p^K" so that $\frac{I^K}{K}_{j,t} = 0$ (Abel, 1981, p.386) - solving for K^* yields Equation 4.23. To calculate the steady-state for capacity set Equation 4.22 equal to zero and solve the resulting quadratic to obtain Equation 4.24.

Equation 4.21 and Equation 4.22 can be rewritten in terms of $\Delta k_{j,t}$ and $\Delta\Omega_{j,t}$ - taking the Taylor expansion around the steady-state of the resulting equations yields the system

Figure E.1: Scatter Plot of Investment in Labour



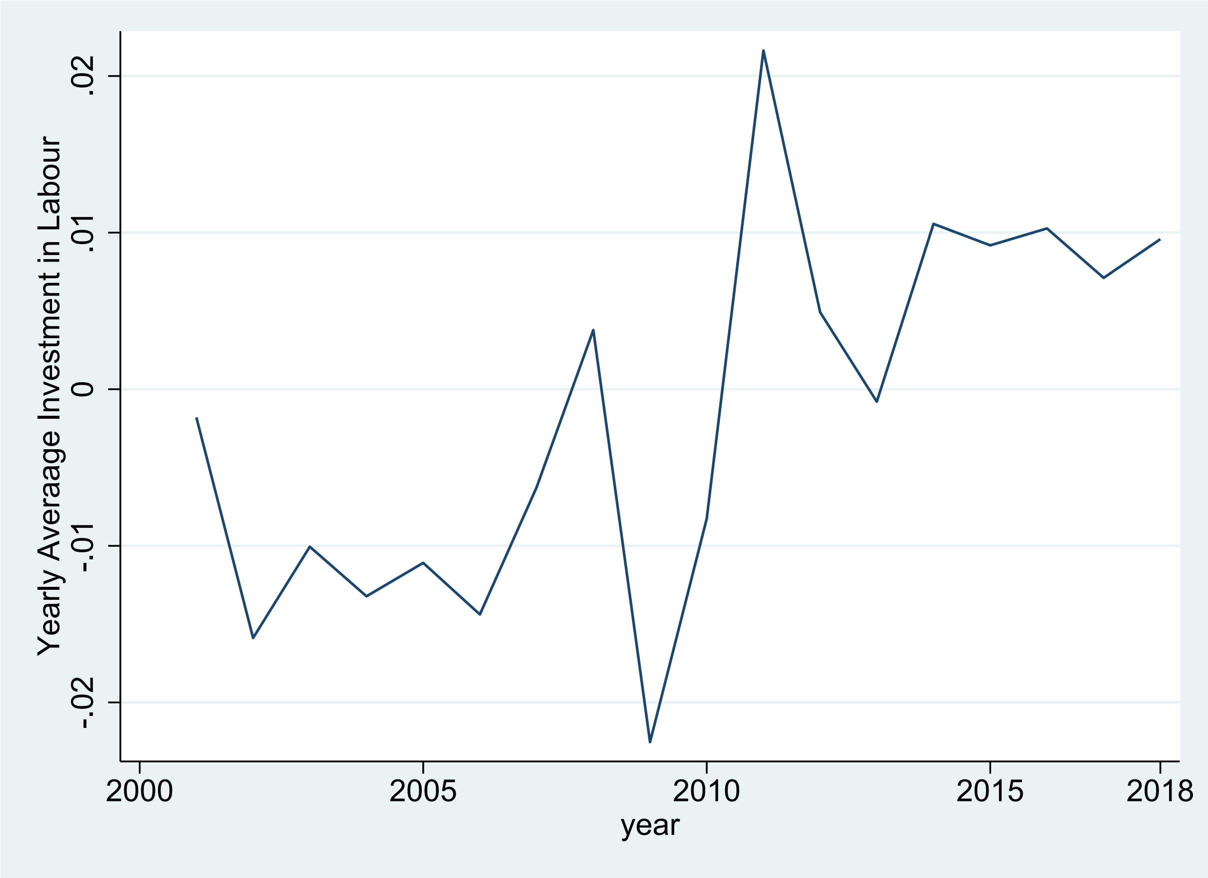
in Equation E.3.

$$\begin{pmatrix} \Delta k_{j,t} \\ \Delta \Omega_{j,t} \end{pmatrix} = \begin{pmatrix} \lambda_1^k & 0 \\ 0 & \lambda_1^\Omega \end{pmatrix} \begin{pmatrix} \Delta k_{j,t-1} \\ \Delta \Omega_{j,t-1} \end{pmatrix} + \begin{pmatrix} \lambda_2^k & \lambda_3^k \\ \lambda_2^\Omega & \lambda_3^\Omega \end{pmatrix} \begin{pmatrix} k_{j,t-1} - k^*_{j,t-1} \\ \Omega_{j,t-1} - \Omega^*_{j,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon^k_{j,t} \\ \epsilon^\Omega_{j,t} \end{pmatrix} \tag{E.3}$$

E.3 Cleaning and Matching the ITS Dataset

Before utilising the ITS dataset, some cleaning and matching techniques are employed. First, firms without a unique identification number are dropped from the sample. For reasons of anonymity, each firm that participates in at least one survey is provided with a unique identification number by the CBI so their responses can be tracked through subsequent survey waves. However, within the dataset a number of survey responses are not paired with a unique identification number. While it could be the case that these survey responses are all generated by one firm there is no guarantee this is true. Therefore,

Figure E.2: Line Plot of Investment in Labour



in order to ensure the highest level of accuracy possible all survey responses without a corresponding unique identification number are dropped.

Second, firm responses recorded as N/A are designated as missing responses. For each trichotomous style question firms have a ”fourth” option: N/A. For example, in the ITS when asked for their expectation for volume of demand firms can reply up, same, down or N/A. Recording these N/A answers as missing ensures calculating the percentages of firm responses to the survey questions are more accurate.

Third, using the Basic Data Section of each survey allows the firm survey responses to be matched to the firm company accounts data contained in the Bureau van Dijk FAME dataset. This matching process is based solely on firm names as this is the only unique firm identifier in the Basic Data Section. This final step creates the matched dataset.