# Quantification of qualitative firm-level survey data*

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July, 2001

**Abstract**

Survey data are widely used to provide indicators of economic activity ahead of the publication of official data. This paper proposes an indicator based on a theoretically consistent procedure for quantifying firm-level survey responses that are ordered and categorical. Firms' survey responses are assumed to be triggered by a latent continuous random variable as it crosses thresholds. Breaking tradition these thresholds are not assumed time invariant. An application to firm-level survey data from the Confederation of British Industry shows that the proposed indicator of manufacturing output growth outperforms traditional indicators that assume time-invariant thresholds.

**Keywords**: Survey data, Forecasting
**JEL classification**: C8, C42, C53

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# 1 Introduction

Survey data, which are often published before official macroeconomic data, are widely used to provide estimators for current, but unknown, macroeconomic variables and indicate likely future movements in the economy.[1] But many surveys offer only a qualitative indication of the current, and expected future, economic condition; published survey data usually record only the proportion of firms who responded to the survey by reporting a "rise", "no change", or a "fall". However, this qualitative survey information, often in conjunction with official macroeconomic data, can be used to extract quantitative indicators of the current state of the economy, and forecasts of the expected future state of the economy.

There are two traditional methods of quantification, the *probability method* of Carlson and Parkin (1975) and the *regression method* of Pesaran (1984).[2] Cunningham, Smith and Weale (1998) offer an alternative approach that relates survey responses to official data by regressing the proportions of firms reporting rises and falls on the official data.[3] In contrast to the regression approach official data, rather than survey data, are used as the regressors. Under the assumption that (after revisions) official data offer unbiased estimates of the state of the economy this avoids problems caused by measurement error of the data.

All three of these approaches exploit only information on the proportion of firms reporting rises and falls to construct a quantitative series. But more information is at hand, even if it is not published, since underlying these proportions is a panel data set recording individual firm-level survey responses. However, firm-level quantification is difficult since there is considerable attrition in the sample.[4] This paper proposes a theoretically consistent "micro" quantification technique that exploits knowledge of firm-level responses, but does not drop any data. Following Cunningham, Smith and Weale (1998) regressions linking the survey responses and official data are motivated by

[1] For example, the Bank of England's Monetary Policy Committee, responsible for setting UK interest rates, uses survey information to help examine inflationary pressures in the economy [see Britton, Cutler and Wardlow, 1999].

[2] For a review, and comparison of these two approaches, see Wren-Lewis, 1985; Smith and McAleer, 1995.

[3] See also Cunningham (1997).

[4] One approach is to consider only those firms that have sufficient time-series observations to justify firm-level estimation, see Mitchell, Smith and Weale (2000).

postulating that firms' categorical responses are triggered by an unobserved continuous latent variable as it crosses thresholds. But in contrast to previous work [Carlson and Parkin, 1975; Cunningham, Smith and Weale, 1998] these thresholds are not assumed time invariant. Exploiting knowledge of firm-level survey responses the thresholds are determined by the type of categorical response given by a firm in the previous period; the firms are grouped according to their previous survey response. In an empirical application using UK industrial survey data from the Confederation of British Industry (CBI) we show that indicators of manufacturing output growth constructed using time-varying thresholds are more accurate than indicators obtained using time-invariant thresholds, where firms are not grouped according to their previous survey responses. Or in other words, disaggregate indicators outperform traditional aggregate indicators.

The plan of this paper is as follows. Section 2 outlines a simple model that relates survey responses and official data. Section 3 shows how firm-level survey data can be used to construct a disaggregate indicator of the official data. Section 4 considers an application to industrial survey data from the CBI. Section 5 makes some concluding comments.

# 2 Relating survey responses to official data

Let firm $i$'s ordered and categorical survey response at time $t$ be determined by a firm-specific unobserved continuous random variable, $y_{it}$, as it crosses thresholds; $i = 1, ..., N_t$, $t = 1, ..., T$. $y_{it}$ is then related to official (economy-wide) macroeconomic data, $x_t$, by assuming the following linear relationship between the survey responses and the official data:[5]

$$y_{it} = x_t + \eta_{it} + \epsilon_{it}, \tag{1}$$

The number of firms, $i$, in the sample at time $t$ can vary across $t$. In (1) $\eta_{it}$ is the difference between $y_{it}$ and $x_t$ anticipated by firm $i$, while $\epsilon_{it}$ is the unanticipated component.

At the end of period $(t-1)$ firm $i$ makes a prediction, $y_{it}^*$, of $y_{it}$ based on macroeconomic information available to all firms, the information set $\Omega_t$. We denote the relevant individual specific information set by $\Omega_t^i$, $i = 1, ..., N_t$. If this prediction is formed rationally

$$y_{it}^* = E\{y_{it}|\Omega_t^i\} = x_t^* + \eta_{it}, \tag{2}$$

[5]See also Cunningham *et al.* (1998).

where $x_t^* = E\{x_t|\Omega_t\}$ is the economy wide rational expectation of $x_t$, and

$$x_t = x_t^* + \zeta_t, \tag{3}$$

where $\zeta_t$ is a white-noise macroeconomic shock unanticipated by firms such that $E\{\zeta_t|\Omega_{t-1}^i\} = 0$.

## 2.1 The observation rules

Industrial surveys typically ask a sample of firms about both their recent experience (retrospective questions) and their expectation of future movements (prospective questions). Firms usually respond by reporting an "up", "no change" or a "down", relative to the previous period. We restrict our attention to these three categorical states.

Retrospective and prospective survey data provide at the firm level two pieces of categorical information on the individual-specific random variable $y_{it}$:

1. a prediction of $y_{it}$ made at the end of period $(t-1)$. The prediction is denoted by the discrete random variable $y_{it,j}^p$, $j = 1, 2, 3$ (corresponding to "up", "no change" and "down", respectively), where

$$y_{it,j}^p = 1 \text{ if } c_{j-1,t}^p < y_{it}^* \leq c_{jt}^p \text{ ; 0 otherwise} \tag{4}$$

   and $c_{jt}^p = \sum_{k=1}^3 \alpha_{jk}^p I\left\{y_{i(t-1),k}^p = 1\right\}$, $\alpha_{jk}^p$ is a fixed coefficient and $I\{.\}$ is an indicator function that is equal to unity when the prediction in the previous period is equal to $k$, $\{k = 1, 2, 3\}$, 0 otherwise.

2. the actual outcome in period $t$. The outcome is denoted by the discrete random variable $y_{it,j}^r$, $j = 1, 2, 3$ where

$$y_{it,j}^r = 1 \text{ if } c_{j-1,t}^r < y_{it} \leq c_{jt}^r \text{ ; 0 otherwise} \tag{5}$$

   and $c_{jt}^r = \sum_{k=1}^3 \alpha_{jk}^r I\left\{y_{i(t-1),k}^r = 1\right\}$, $\alpha_{jk}^r$ is a fixed coefficient and $I\{.\}$ is an indicator function that is equal to unity when the outcome in the previous period is equal to $k$, $\{k = 1, 2, 3\}$, 0 otherwise.

We follow convention and assume $\{c_{0t}^p, c_{0t}^r\} = -\infty$ and $\{c_{3t}^p, c_{3t}^r\} = \infty$. Note that the thresholds $(c_{j-1,t}^p, c_{jt}^p)$ and $(c_{j-1,t}^r, c_{jt}^r)$ are invariant with respect to individuals, $i$, but can vary according to time, $t$. This contrasts the time-invariant, and symmetric (i.e. $-c_1 = c_2$), thresholds integral to the widely used Carlson and Parkin (1975) quantification technique. The thresholds in (4) and (5) are determined by the type of categorical response given by a firm in the previous period. This groups the firms according to their previous survey response. The grouping is flexible in the sense that firms can move in and out of the three groups as they change their qualitative responses to the question over time. Note that the thresholds also differ between the retrospective and prospective surveys.

Defined with respect to the error terms in (1) the observation rules become respectively:[6]

- Prospective information:

$$y^p_{it,j} = 1 \text{ if } c^p_{j-1,t} - x^*_t < \eta_{it} \leq c^p_{jt} - x^*_t; j = 1, 2, 3 \tag{6}$$

- Retrospective information:

$$y^r_{it,j} = 1 \text{ if } c^r_{j-1,t} - x_t < \eta_{it} + \epsilon_{it} \leq c^r_{jt} - x_t; j = 1, 2, 3 \tag{7}$$

with zero observed otherwise in both cases.

# 3 Proportion methods

In this paper we follow Cunningham, Smith and Weale (1998) and use so-called *proportion methods*[7] to obtain indicators of current, but unavailable, official data. Proportion methods group the survey data of categorical responses by calculating across time the proportion of firms that respond similarly in the survey. Grouping the data enables us to consider all of the survey information, even in a panel data set consisting of observations recording

[6] Distributional assumptions are made below about the errors, $\eta_{it}$ and $\eta_{it}+\epsilon_{it}$. The uniform and logistic functions are convenient, offering closed form density functions. But we can only motivate the logistic function if we view the logistic function as an approximation to the cumulative normal distribution [the cumulative normal and logistic distributions are in fact similar, except that the logistic distribution has slightly heavier tails]. Otherwise it is inconsistent to assume $\eta_{it}$ and $\eta_{it} + \epsilon_{it}$ have the same distribution.

[7] See Amemiya (1985), pp. 275-278.

across time a sample of firms' survey responses where there is considerable missing data as firms do not always respond to the survey. Previous studies using firm-level survey data have either ignored the time dimension and used cross-sectional techniques to analyse firms' behaviour at a given point in time [see Nerlove, 1983; Horvath, Nerlove and Willson, 1992] or have excluded those firms plagued by missing data and taken cross-sectional averages of firm-specific time-series [see Mitchell, Smith and Weale, 2000].

We give a probabilistic foundation to the observation rules (6) and (7), by letting the scaled error terms $\{\sigma_p \eta_{it}\}$ and $\{\sigma_r(\eta_{it}+\epsilon_{it})\}$, where $\{\sigma_p, \sigma_r\} > 0$, possess common and known *cumulative distribution functions* (CDFs), $F_\eta(.)$ and $F_{\eta\epsilon}(.)$, respectively, $i = 1, ..., N_t$, which are parameter free and are assumed time-invariant. Then,

$$\mathcal{P}\{y^p_{it,j} = 1 | y^p_{i(t-1),k} = 1, x^*_t\} = F_\eta(\mu^p_{jk} - \sigma_p x^*_t) - F_\eta(\mu^p_{j-1,k} - \sigma_p x^*_t), \quad (8)$$

where $\mu^p_{jk} = \sigma_p \alpha^p_{jk}$, and

$$\mathcal{P}\{y^r_{it,j} = 1 | y^r_{i(t-1),k} = 1, x_t\} = F_{\eta\epsilon}(\mu^r_{jk} - \sigma_r x_t) - F_{\eta\epsilon}(\mu^r_{j-1,k} - \sigma_r x_t), \quad (9)$$

where $\mu^r_{jk} = \sigma_r \alpha^r_{jk}$, $\{j, k = 1, 2, 3\}$.

## 3.1 Prospective survey information

Define the prospective survey *disaggregate* proportion of firms that gave response $j$ at time $t$ given that they gave response $k$ at time $(t-1)$

$$P^p_{t,jk} = (1/N^p_{kt}) \sum_{i=1}^{N^p_{kt}} \left( y^p_{it,j} \times y^p_{i(t-1),k} \right), \ \{j, k = 1, 2, 3\}, \quad (10)$$

where $N^p_{kt} = \sum_{i=1}^{N_t} y^p_{i(t-1),k}$, denotes the total number of firms that gave the $k-$th response at time $(t-1)$. As $E\{y^p_{it,j} = 1 | y^p_{i(t-1),k} = 1, x^*_t\} = F_\eta(\mu^p_{jk} - \sigma_p x^*_t) - F_\eta(\mu^p_{j-1,k} - \sigma_p x^*_t)$, $E\{P^p_{t,jk} | x^*_t\} = F_\eta(\mu^p_{jk} - \sigma_p x^*_t) - F_\eta(\mu^p_{j-1,k} - \sigma_p x^*_t)$. If we further assume that the CDF $F_\eta(.)$ is *symmetric*, then $E\{P^p_{t,1k} | x^*_t\} = F_\eta(\mu^p_{1k} - \sigma_p x^*_t)$ and $E\{P^p_{t,3k} | x^*_t\} = F_\eta[-(\mu^p_{2k} - \sigma_p x^*_t)]$.

Assuming the sample observations $P^p_{t,1k}$ and $P^p_{t,3k}$ are drawn from a multinomial population we may define the non-linear regressions

$$P^p_{t,1k} = F_\eta(\mu^p_{1k} - \sigma_p x^*_t) + \xi^p_{t,1k},$$

$$P^p_{t,3k} = F_\eta[-(\mu^p_{2k} - \sigma_p x^*_t)] + \xi^p_{t,3k}, \tag{11}$$

such that

$$(N^p_{kt})^{1/2}\begin{pmatrix}\xi^p_{t,1k}\\ \xi^p_{t,3k}\end{pmatrix} \to^L \left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}F_{\eta 1k,t}(1-F_{\eta 1k,t}) & -F_{\eta 1k,t}F_{\eta 3k,t}\\ -F_{\eta 1k,t}F_{\eta 3k,t} & F_{\eta 3k,t}(1-F_{\eta 3k,t})\end{pmatrix}\right),$$

where $F_{\eta 1k,t} = F_\eta(\mu^p_{1k} - \sigma_p x^*_t)$ and $F_{\eta 3k,t} = 1 - F_\eta(\mu^p_{2k} - \sigma_p x^*_t)$. Note that, conditional on the recorded response in the previous period, restricting ourselves to categories $j = 1$ and $j = 3$ results in no loss of information since $\sum_{j=1}^3 P^p_{t,jk} = 1$.

Assuming $F_\eta(.)$ is strictly monotonic it has an inverse. The non-linear regressions are simplified by taking a Taylor series approximation to $F_\eta^{-1}(P^p_{t,1k})$ and $F_\eta^{-1}(P^p_{t,3k})$ about $F_\eta(\mu^p_{1k}-\sigma_p x^*_t)$ and $F_\eta[-(\mu^p_{2k}-\sigma_p x^*_t)]$ respectively, yielding the *asymptotic* ($N^p_{kt} \to \infty$) linear regression models

$$F_\eta^{-1}(P^p_{t,1k}) = \mu^p_{1k} - \sigma_p x^*_t + u^p_{t,1k},$$

$$F_\eta^{-1}(P^p_{t,3k}) = -\mu^p_{2k} + \sigma_p x^*_t + u^p_{t,3k}, \tag{12}$$

where

$$u^p_{t,1k} = f^{-1}_{\eta 1k,t}\xi^p_{t,1k} + o_p(N^{p\,-1}_{kt}),$$
$$u^p_{t,3k} = f^{-1}_{\eta 3k,t}\xi^p_{t,3k} + o_p(N^{p\,-1}_{kt}), \tag{13}$$

and $f_{\eta 1k,t} = f_\eta(\mu^p_{1k} - \sigma_p x^*_t)$, $f_{\eta 3k,t} = f_\eta[-(\mu^p_{2k} - \sigma_p x^*_t)]$ and $f_\eta(z) = dF_\eta(z)/dz$ is the common *density* function of $\{\eta_{it}\}_{i=1}^{N^p_{kt}}$.

Substituting (3) into (12) yields the (semi) disaggregate regressions[8]

$$F_\eta^{-1}(P^p_{t,1k}) = \mu^p_{1k} - \sigma_p x_t + \tau^p_{t,1k},$$

$$F_\eta^{-1}(P^p_{t,3k}) = -\mu^p_{2k} + \sigma_p x_t + \tau^p_{t,3k}, \tag{14}$$

where $\tau^p_{t,1k} = (-\sigma_p\zeta_t + u^p_{t,1k})$ and $\tau^p_{t,3k} = (\sigma_p\zeta_t + u^p_{t,3k})$. Since $\zeta_t$ is $O_p(1)$, but $u^p_{t,1k}$ and $u^p_{t,3k}$ are $O_p(N^{p\,-1/2}_{kt})$, the errors in (14) are asymptotically

[8] Although based on firm-level information these regressions are not firm-specific and it is in this sense we call the regressions "semi" disaggregate.

dominated by the white-noise error $\zeta_t$. Given an assumed CDF, (14) are estimated for a given $k$ by generalised instrumental variables (IV) [see Sargan, 1958], with $x_t$ instrumented by lagged values of $x_t$.[9]

To contrast (14), based on the time-varying thresholds (4) and (5), with traditional time-invariant thresholds, as used by Cunningham, Smith and Weale (1998), we also consider "aggregate" proportions. The aggregate proportions are based on the number of firms recording response $j$ at time $t$: $P^p_{t,j} = N_t^{-1} \sum_{i=1}^{N_t} y^p_{it,j}$. Assuming $c^p_{jt} = c^p_j$ *aggregate* regressions corresponding to the disaggregate regression model, (14), are readily defined.

## 3.2 Retrospective survey information

Define the retrospective survey *disaggregate* proportion of firms that gave response $j$ at time $t$ given that they gave response $k$ at time $(t-1)$

$$P^r_{t,jk} = (1/N^r_{kt}) \sum_{i=1}^{N^r_{kt}} \left( y^r_{it,j} \times y^r_{i(t-1),k} \right), \ \{j,k = 1,2,3\}, \tag{15}$$

where $N^r_{kt} = \sum_{i=1}^{N_t} y^r_{i(t-1),k}$, denotes the total number of firms that gave the $k-$th response at time $(t-1)$. Then define the asymptotic (semi) disaggregate linear regression models corresponding to (12)

$$\begin{aligned} F^{-1}_{\eta\epsilon}(P^r_{t,1k}) &= \mu^r_{1k} - \sigma_r x_t + u^r_{t,1k}; \\ F^{-1}_{\eta\epsilon}(P^r_{t,3k}) &= -\mu^r_{2k} + \sigma_r x_t + u^r_{t,3k} \end{aligned} \tag{16}$$

The error terms $\mathbf{u}_{1k} = (u^r_{1,1k}, u^r_{2,1k}, ..., u^r_{T,1k})'$ and $\mathbf{u}_{3k} = (u^r_{1,3k}, u^r_{2,3k}, ..., u^r_{T,3k})'$ are assumed to be white noise processes where $E(\mathbf{u}_{ik}\mathbf{u}'_{jk}) = \sigma_{ijk}\mathbf{I}_T$; for a given $k$ (16) is considered as two seemingly unrelated regression equations.[10] As

[9] In the empirical application below we consider the uniform and the logistic CDFs, leading to the linear probability model (LPM) and the logit model, respectively.

[10] We also considered error terms $(u^r_{t,1k}, u^r_{t,3k})$ with a multinomial variance-covariance matrix

$$(N^r_{kt})^{1/2} \begin{pmatrix} u^r_{t,1k} \\ u^r_{t,3k} \end{pmatrix} \to^L \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} f^{-2}_{\eta\epsilon 1k,t} F_{\eta\epsilon 1k,t}(1 - F_{\eta\epsilon 1k,t}) & f^{-1}_{\eta\epsilon 1k,t} f^{-1}_{\eta\epsilon 3k,t} F_{\eta\epsilon 1k,t} F_{\eta\epsilon 3k,t} \\ f^{-1}_{\eta\epsilon 1k,t} f^{-1}_{\eta\epsilon 3k,t} F_{\eta\epsilon 1k,t} F_{\eta\epsilon 3k,t} & f^{-2}_{\eta\epsilon 3,t} F_{\eta\epsilon 3k,t}(1 - F_{\eta\epsilon 3k,t}) \end{pmatrix} \right]$$

where $f_{\eta\epsilon 1k,t} = f_{\eta\epsilon}(\mu^r_{1k} - \sigma_r x_t)$, $f_{\eta\epsilon 3k,t} = f_{\eta\epsilon}(-\mu^r_{2k} + \sigma_r x_t)$, $F_{\eta\epsilon 1k,t} = F_{\eta\epsilon}(\mu^r_{1k} - \sigma_r x_t)$ and $F_{\eta\epsilon 3k,t} = 1 - F_{\eta\epsilon}(\mu^r_{2k} - \sigma_r x_t)$. Since $x_t$ is observed for a given $k$ feasible and asymptotically efficient estimation of (16) was achieved by generalised least squares (or *minimum chi-squared*) estimation, given the structure of the variance-covariance matrix. But this model above, aggregate regressions corresponding to (16) are readily defined using the aggregate proportions $P^r_{t,j} = N_t^{-1} \sum_{i=1}^{N_t} y^r_{it,j}$ and assuming $c^r_{jt} = c^r_j$.

### 3.3 Solving for $x_t$

Disaggregate (aggregate) indicators of the official (economy-wide) macroeconomic data, $x_t$, are derived from the estimated semi disaggregate (aggregate) regressions in both the prospective and retrospective cases. This is achieved as follows. Consider, for expositional purposes only, the retrospective semi-disaggregate regression model, (16). Then

$$\widehat{x_{1kt}} = \frac{-F_{\eta\epsilon}^{-1}(P^r_{t,1k}) + \widehat{\mu^r_{1k}}}{\widehat{\sigma_r}}; \widehat{x_{2kt}} = \frac{F_{\eta\epsilon}^{-1}(P^r_{t,3k}) + \widehat{\mu^r_{2k}}}{\widehat{\sigma_r}}. \tag{17}$$

where $\widehat{}$ denotes the coefficient estimates. The disaggregate indicator is obtained by reconciling the estimates $\widehat{x_{1kt}}$ and $\widehat{x_{2kt}}$, $\forall k$, using their associated variance-covariance matrix [see Stone, Champernowne and Meade, 1942]. The aggregate indicator requires two estimates of $x_t$ to be reconciled.

## 4 An application using CBI survey data

### 4.1 The Industrial Trends Survey

The CBI's *Industrial Trends Survey* (ITS), conducted quarterly, gives qualitative opinion from UK manufacturing firms on past and expected trends in output, exports, prices, costs, investment intentions, business confidence and capacity utilisation. In our application we consider the categorical responses to the following three questions in the ITS:

1. "Excluding seasonal variations, what has been the trend over the past four months with regard to volume of output?". Firms can respond either "up", "same", "down" or "not applicable".

2. "Excluding seasonal variations, what are the expected trends for the next four months with regard to volume of output?". Firms can respond either "up", "same", "down" or "not applicable".

is not considered below since it failed the specification test discussed in Section 4.2.1; the assumed symmetry of the CDF was statistically rejected. It is not appropriate to assume our sample is drawn from a multinomial population. Noise in the sample (types of error distinct from sampling error) may explain this finding.

3. “Are you more, or less, optimistic than you were four months ago about the general business situation in your industry?”. Firms can respond either “more”, “same” or “less”.

The first question is retrospective, the second prospective, while the third could be informative about either past or future output movements. The ITS is widely used to derive quantitative indicators of output movements in the UK economy [see *inter alia* Lee, 1994; Britton, Cutler and Wardlow, 1999]. Quantification traditionally exploits information on the proportion of firms reporting rises or falls. In contrast in our application we consider firm level responses to the ITS enabling us to compare the disaggregate indicators with the more traditional aggregate indicators.

We consider firm level responses to the ITS from October 1988 to October 1997. Responses are available in January, April, July and October. These responses are matched to quarterly official macroeconomic data $x_t$, specifically manufacturing output growth (seasonally adjusted), by assuming that they correspond to the period 1988q3–1997q3. For example, the January survey represents information formed before any first quarter information became available to firms and is therefore matched to the fourth quarter of the previous year.[11] Our data set records in total 43,936 responses to the ITS. 5002 firms are sampled in total from October 1988 to October 1997. There are, on average, 1183 firms in the sample at time $t$, and 8.7 time-series observations per firm. The number of firms that answered “not applicable” was very small and is ignored in later analysis.

## 4.2 Aggregate and disaggregate indicators of manufacturing output growth

Aggregate and disaggregate regressions are estimated in an unrestricted form; the slope coefficients are not restricted to be of equal and opposite sign so that this assumption can be tested. Let $a_j$ and $b_j$ denote the estimated intercept and slope coefficients for the aggregate regressions, and $a_{jk}$ and $b_{jk}$ their disaggregate counterparts. Estimation is over the period 1988q4-1997q3 (36 time-series observations) in the retrospective case and 1989q1-1997q4 using

[11] There is a one month overlap on each survey as firms are asked to report over a four month period four times a year. But as their responses are qualitative this is unlikely to be important.

the prospective information. In the prospective case $x_{t-1}$ and $x_{t-2}$ are used as instruments for $x_t$.[12]

### 4.2.1 Indicator performance

Tables 1 and 2 examine the accuracy of the estimates of manufacturing output (MQ) growth implied by the retrospective and prospective regressions. They report the root mean squared forecast errors [RMSFE] for the aggregate (agg) and disaggregate (Disagg) indicators against the outturns, $x_t$. To reflect the importance of firm size results are also presented in parentheses where firms' responses are weighted by sales volumes. These weights, made available by the CBI, are time-varying.

**Table 1 : RMSFE - retrospective data (weighted figures in parentheses)**

| Model | vol of output | business conf |
|---|---|---|
| Agg. LPM | 3.511 (4.101) | 6.445 (6.122) |
| Agg. logit | 3.780 (4.553) | 6.588 (6.373) |
| Disagg. LPM | 2.820 (3.306) | 6.062 (6.280) |
| Disagg. logit | 2.875 (3.513) | 5.107 (5.429) |

Table 1 shows that the disaggregate indicators constructed using the retrospective volume of output responses leads to better implied estimates of MQ growth than their aggregate counterparts. The business confidence responses do not offer as good estimates of MQ growth. Comparison of Tables 1 and 2 reveals that business confidence responses are more informative prospectively. However, Table 2 indicates that the prospective volume of output responses are more informative than the business confidence responses. Interestingly, volume of output is more informative prospectively than retrospectively.

**Table 2 : RMSFE - prospective data (weighted figures in parentheses)**

| Model | vol of output | business conf |
|---|---|---|
| Agg. LPM | 2.608 (2.998) | 3.227 (3.039) |
| Agg. logit | 2.675 (3.181) | 3.281 (3.106) |
| Disagg. LPM | 2.362 (3.116) | 2.976 (2.920) |
| Disagg. logit | 2.414 (3.098) | 2.790 (2.828) |

[12]Results are qualitatively robust to the choice of instruments.

Weighting the firms according to their sales volumes leads to worse results for volume of output. However, there can be an improvement when using the business confidence data. Henceforth, for brevity we confine our attention to the unweighted figures.

To facilitate interpretation of the above results Appendices A and B present the details of estimating the underlying linear regressions: Appendix A reports the aggregate and disaggregate regression results using retrospective volume of output responses, while Appendix B reports the aggregate and disaggregate regression results using prospective volume of output responses. For comparative purposes the appendices also present the corresponding regressions using the business confidence survey responses. Two tests for serial correlation in the residuals are considered in the retrospective case: the lagrange multiplier (LM) test for first order serial correlation and the Durbin-Watson (DW) statistic. The DW statistic is appropriate when $E(\eta_{it} \mid x_{t+j}) = 0$; $j \leq 0$. In the prospective case we use the LM test.[13] Let us summarise the main findings from Appendices A and B:

1. The slope coefficients in the regressions are positive and significant when $j = 1$ (an "up"), and statistically negative for $j = 3$ (a "down"). This is consistent with priors; a rise in manufacturing output growth leads to a rise (fall) in the proportion of firms reporting a rise (fall).

2. The poorer performance for business confidence in Tables 1 and 2 is explained by less explanatory power (lower $R^2$s) for the business confidence regressions. This holds in both the prospective and retrospective cases.

3. The volume of output survey responses are better related to the official data than the business confidence data; the $t$-values associated with the slope coefficients are in general higher for volume of output than business confidence.

4. Despite the volume of output responses offering a better indicator prospectively than retrospectively the $t$-statistics on the intercept and slope coefficients are lower prospectively, providing some evidence consistent with the view that we would expect there to be more uncertainty

[13] The LM test for first order serial correlation in IV regressions is presented, see Breusch and Godfrey (1981).

prospectively than retrospectively; expectations of output growth are likely to be more diffuse than reports of past experience

5. The point estimates for the coefficient on $x_t$ often lie close to zero. Examination of (17) shows that as $\widehat{\sigma_r}$ or $\widehat{\sigma_p}$ approaches zero the implied series becomes extremely volatile. Therefore it is no surprise that the "recovered" estimates in Tables 1 and 2 may be a worse fit for the actual series than would be its mean value. For comparative purposes, the standard deviation of MQ about its mean is 3.7 for both the retrospective and prospective cases.

We test the importance of using semi-disaggregate rather than aggregate regressions in two ways. First, we perform a Wald test for state dependence. Recall that (4) and (5) allow firm $i$'s response in period $t$ to depend on its response in period $(t-1)$. A natural test for serial, or state, dependence is therefore to test $\alpha^p_{j1} = \alpha^p_{j2} = \alpha^p_{j3}$ and $\alpha^r_{j1} = \alpha^r_{j2} = \alpha^r_{j3}$ for $j = 1$ and $j = 3$ by performing a Wald test for $a_{j1} = a_{j2} = a_{j3}$, for $j = 1$ and $j = 3$. These equalities are rejected with a $p$-value of zero for all regressions implying state dependence; thresholds vary according to the type of response given in the previous period. In other words optimists (firms that reported an "up" in the previous period) and pessimists (firms that reported a "down" in the previous period) do not share the same thresholds. Second, we investigate the importance of introducing dynamics by testing for serial correlation in the disaggregate and aggregate regressions. In general the retrospective disaggregate regressions display less serial correlation than the aggregate regressions in the retrospective case. This is consistent with the view that serial correlation is evidence of incorrectly omitting dynamics. It is therefore important to consider firm level survey responses. In the prospective case there is no evidence of serial correlation in either the aggregate or disaggregate regressions.

Next we provide a specification test for the aggregate and disaggregate regressions by testing the assumed symmetry of the CDF: a Wald test was performed for the restriction $b_{1k} + b_{3k} = 0$. Tables 3 and 4 show that the evidence is, in general, supportive of symmetry. Crucially, the disaggregate regressions are well specified *vis-à-vis* the micro-econometric foundations outlined above in Sections 2 and 3. Note that even in the presence of asymmetry the regressions still have validity as an *ad hoc* specifications; the informational content of the regressions remain intact.[14] It suggests that there are sources of "error" over and above sampling error linking the survey data and output movements. These may include "mismatch". The firms may operate in part outside manufacturing industry.

**Table 3 : Wald test for symmetry: aggregate regressions, p-values**

| | vol of output | | business conf | |
|---|---|---|---|---|
| | LPM | Logit | LPM | Logit |
| retrospective | 0.002 | 0.214 | 0.061 | 0.153 |
| prospective | 0.996 | 0.966 | 0.025 | 0.124 |

**Table 4 : Wald test for symmetry: disaggregate regressions, p-values**

| | | vol of output | | business conf | |
|---|---|---|---|---|---|
| | k | LPM | Logit | LPM | Logit |
| retrospective | up | 0.189 | 0.025 | 0.295 | 0.150 |
| | same | 0.017 | 0.552 | 0.062 | 0.332 |
| | down | 0.003 | 0.015 | 0.309 | 0.006 |
| prospective | up | 0.913 | 0.010 | 0.379 | 0.146 |
| | same | 0.002 | 0.000 | 0.048 | 0.329 |
| | down | 0.106 | 0.025 | 0.344 | 0.022 |

### 4.2.2 Encompassing Tests

Tables 1 and 2 show (semi) disaggregation to lead to better indicators of manufacturing output growth, in the sense of lower RMSFEs. But RMSFEs do not compare the indicators against plausible alternatives. Therefore we test whether the indicators obtained using the survey data models add information [see Granger and Ramanathan, 1984] *vis à vis* two alternative models. The first model considered, *con*, is simply the mean growth rate of MQ over the period. The second model examined, AR(1), takes the fitted values from a first order autoregression with drift estimated in the growth

[14] For a discussion of asymmetric distributions see Smith, 1989.

rate of MQ. We confine attention to the survey data models using the volume of output responses which were shown in Tables 1 and 2 to offer more accurate indicators than the business confidence responses.

We ran OLS regressions of the form: $x_t = \Theta_1 \widehat{x}_t^s + \Theta_2 \widehat{x}_t^i$ where $x_t$ is actual MQ growth, $\widehat{x}_t^s$ is MQ growth implied by the survey model, and $\widehat{x}_t^i$ is the fitted value from the alternative model. The estimated coefficients in these regressions, $\widehat{\Theta}_1$ and $\widehat{\Theta}_2$, show how the information from the survey model and the alternative model should be combined to provide the best estimates of MQ growth: $\widehat{\Theta}_1$ and $\widehat{\Theta}_2$ tell us the weights that should be attached to the survey and alternative models. When considering *con* as the alternative model $\Theta_1 + \Theta_2 = 1$ because $\widehat{x}_t^s$ shares the same mean as $x_t$.

If we consider the survey data to consist of two components, the truth and measurement error, then the finding that, for example, $\Theta_1 \to 0$ could be attributed to measurement error (noise) in the survey.[15] We also test the following hypotheses: $H_A : \Theta_1 = 1, \Theta_2 = 0$ and $H_B : \Theta_1 = 0, \Theta_2 = 1$. The first hypothesis, $A$, tests whether the survey model encompasses the alternative model, and the second hypothesis, $B$, tests if the alternative model encompasses the survey model.

**Table 5 : Encompassing test - retrospective data**

| | con | | | | AR(1) | | | |
|---|---|---|---|---|---|---|---|---|
| Survey Model | $\widehat{\Theta}_1$ | $\widehat{\Theta}_2$ | $H_A$ | $H_B$ | $\widehat{\Theta}_1$ | $\widehat{\Theta}_2$ | $H_A$ | $H_B$ |
| Agg: LPM | 0.520 (0.086) | 0.480 (0.599) | 0.000 | 0.000 | 0.503 (0.122) | 0.094 (0.308) | 0.000 | 0.000 |
| Agg: Logit | 0.483 (0.086) | 0.517 (0.621) | 0.000 | 0.000 | 0.450 (0.122) | 0.155 (0.321) | 0.000 | 0.001 |
| Disagg: LPM | 0.626 (0.083) | 0.374 (0.529) | 0.000 | 0.000 | 0.578 (0.100) | 0.231 (0.230) | 0.000 | 0.000 |
| Disagg: Logit | 0.617 (0.083) | 0.383 (0.535) | 0.000 | 0.000 | 0.567 (0.100) | 0.240 (0.232) | 0.000 | 0.000 |

Notes: For each null hypothesis, $A$ or $B$, we report the $p$-value of failing to reject the null hypothesis. Estimated standard errors are in parentheses.

[15] For further discussion of the role of measurement error in the quantification of survey data see Lee (1994).

**Table 6** : **Encompassing test - prospective data**

| Survey Model | con $\widehat{\Theta}_1$ | con $\widehat{\Theta}_2$ | con $H_A$ | con $H_B$ | AR(1) $\widehat{\Theta}_1$ | AR(1) $\widehat{\Theta}_2$ | AR(1) $H_A$ | AR(1) $H_B$ |
|---|---|---|---|---|---|---|---|---|
| Agg: LPM | 0.881 (0.154) | 0.119 (0.735) | 0.741 | 0.000 | 0.800 (0.200) | 0.197 (0.303) | 0.605 | 0.000 |
| Agg: Logit | 0.902 (0.168) | 0.098 (0.758) | 0.844 | 0.000 | 0.820 (0.227) | 0.181 (0.326) | 0.728 | 0.001 |
| Disagg: LPM | 0.919 (0.134) | 0.081 (0.667) | 0.833 | 0.000 | 0.887 (0.174) | 0.174 (0.274) | 0.800 | 0.000 |
| Disagg: Logit | 0.924 (0.141) | 0.076 (0.683) | 0.865 | 0.000 | 0.897 (0.186) | 0.070 (0.287) | 0.845 | 0.000 |

Notes: see notes to Table 5.

Table 5 shows that the retrospective survey data contains significant information against both the *con* and AR(1) alternatives; we always statistically reject $\Theta_1 = 0$ but cannot reject $\Theta_2 = 0$. Against the *con* alternative $\widehat{\Theta}_1$ is higher for the disaggregate regressions; this reflects the finding in Table 1 that the RMSFE are lower for the disaggregate regressions. There is no evidence that the survey models encompass the alternative models; there remains some informational content in the alternative model.

In contrast, Table 6 reveals that in the prospective case both the aggregate and disaggregate regressions encompass the alternatives. The disaggregate regressions offer the most information relative to the alternatives. $\widehat{\Theta}_1$ and $H_A$ are higher for the disaggregate than the aggregate regressions.

### 4.2.3 Steady state properties

This section examines the characteristics of the steady state implicit in the dynamics embodied within the disaggregate regressions. The steady state proportions of the disaggregate regressions, as a function of the growth rate, are given by the eigenvector, $\mathbf{v}_t$, associated with the unit eigenvalue of the transition matrix $\mathbf{M}_t$ where

$$\mathbf{M}_t = \begin{bmatrix} F_{11t} & F_{12t} & F_{13t} \\ F_{21t} & F_{22t} & F_{23t} \\ F_{31t} & F_{32t} & F_{33t} \end{bmatrix}, \tag{18}$$

and $F_{jkt}$ is the proportion of firms in state $j$ at time $t$ given that they were in state $k$ at time $(t-1)$. Given $a_{jk}$ and $b_{jk}$ we compute $\mathbf{M}_t$ for $x_t = \{-8, -7, ..., -1, 0, 1, ..., 7, 8\}$. The first element of $\mathbf{v}_t$ gives the proportion of firms reporting a 1, an "up" $(U)$, the second element the proportion reporting a 2, "no change" $(S)$, and the third and final element the proportion reporting a 3, a "down" $(D)$.

Fig 1: Steady state proportions as a function of MQ growth using the volume of output survey responses

Figure 1 shows the steady state proportions as a function of the growth rate for both linear and logistic models in the retrospective and prospective cases using the volume of output responses. While we do not have any clear quantitative view of the way the steady-state proportions should be linked to the growth rate, there are clear qualitative properties one should look for. As the growth rate rises from a low negative value, one would expect both the proportions reporting no change and those reporting a rise in their volume of output to increase. Beyond a particular point the steady state proportion reporting no change should be expected to start falling again, while the proportion reporting a rise should continue to increase. The proportion reporting a fall should be expected to be a declining function of the growth rate.

We can see that the logistic models have the expected properties. The linear models are less satisfactory since the proportion reporting "no change" is, in both the retrospective and prospective cases, an increasing function of the growth rate. In the prospective case the proportion reporting "no change" is an increasing function of the growth rate not only over the range shown in the charts but over the whole range for which the models give permissible values, between 0 and 1, for all three proportions. Thus, while the linear and logistic models are little different in terms of their capacity to explain the data, they are very different in terms of their dynamic properties, with the logistic models being preferred.

#### 4.2.4 An improved prospective estimator

Tables 1 and 2 showed that the business confidence survey data led to better estimates of MQ growth prospectively than retrospectively. To investigate the advantages of considering the business confidence data prospectively, in addition to the volume of output data, we reconciled the implied series generated by both responses. Table 7 reports the RMSFE when considering the volume of output and business confidence survey responses together.

**Table 7 : RMSFE - combined prospective data**

| | vol of output+bus conf |
|---|---|
| Agg. LPM | 2.599 |
| Agg. logit | 2.622 |
| Disagg. LPM | 1.999 |
| Disagg. logit | 2.156 |

Combining the volume of output and business confidence survey responses results in estimates of expected MQ growth closer to the outturns. Table 8 then shows that the pooled disaggregate indicator encompasses the alternative models more convincingly than its aggregate counterpart.

**Table 8 : Encompassing test - combined prospective data**

| | con | | | | AR(1) | | | |
|---|---|---|---|---|---|---|---|---|
| Survey Model | $\hat{\Theta}_1$ | $\hat{\Theta}_2$ | $H_A$ | $H_B$ | $\hat{\Theta}_1$ | $\hat{\Theta}_2$ | $H_A$ | $H_B$ |
| Agg: LPM | 0.877 (0.152) | 0.123 (0.732) | 0.723 | 0.000 | 0.800 (0.197) | 0.192 (0.302) | 0.597 | 0.000 |
| Agg: Logit | 0.880 (0.156) | 0.120 (0.739) | 0.744 | 0.000 | 0.798 (0.203) | 0.199 (0.306) | 0.608 | 0.000 |
| Disagg: LPM | 0.967 (0.110) | 0.033 (0.566) | 0.956 | 0.000 | 0.965 (0.138) | 0.009 (0.226) | 0.957 | 0.000 |
| Disagg: Logit | 0.948 (0.120) | 0.052 (0.609) | 0.909 | 0.000 | 0.924 (0.151) | 0.065 (0.244) | 0.880 | 0.000 |

Notes: see notes to Table 5.

# 5 Concluding comments

This paper demonstrates the benefits of considering firm-level responses to industrial surveys. The proposed disaggregate indicators lead to more informative, or less noisy, estimates of (unknown) MQ growth than aggregate indicators based on the traditional approach of considering only the proportion of firms reporting a rise, or a fall. Encompassing tests show that survey information helps with an assessment about the state of the economy and that a stronger signal is recovered from the disaggregate model than is available from the aggregate data. The dynamic character of the disaggregate models allows us to estimate the steady state responses to the questions in the survey as functions of the underlying growth rate. We show that, while there is little to choose between linear and logistic models in terms of linking the data to the survey, the steady state properties of the logistic models are much more satisfactory than those of the linear models. This offers a clear reason for preferring the logistic models.

# A Tables of Regression Results using Retrospective Survey Data[16]

**Table A1: Aggregate regressions: Volume of output**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_1$ | 0.240 | 0.011 | 21.905 | -1.215 | 0.062 | -19.513 |
| $b_1$ | 0.014 | 0.003 | 4.833 | 0.087 | 0.017 | 5.209 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.407 | 0.065 | 0.797/13.407 | 0.444 | 0.366 | 0.872/11.882 |
| $a_3$ | 0.267 | 0.012 | 22.876 | -1.071 | 0.062 | -17.179 |
| $b_3$ | -0.019 | 0.003 | -5.954 | -0.094 | 0.017 | 0.017 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.510 | 0.069 | 1.011/9.268 | 0.482 | 0.367 | 0.918/10.809 |

[16] $R^2$ denotes the coefficient of determination, $\sigma$ the standard error of the regression, $DW$ the Durbin-Watson statistic and $LM$ the lagrange-multiplier statistic for first order serial correlation.

**Table A2: Disaggregate regressions:Volume of output**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_{11}$ | 0.472 | 0.011 | 42.914 | -0.118 | 0.045 | -2.618 |
| $b_{11}$ | 0.011 | 0.003 | 3.895 | 0.047 | 0.012 | 3.931 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.309 | 0.065 | 1.432/2.583 | 0.313 | 0.264 | 1.455/2.364 |
| $a_{31}$ | 0.132 | 0.008 | 17.271 | -1.971 | 0.070 | -28.100 |
| $b_{31}$ | -0.009 | 0.002 | -4.329 | -0.074 | 0.019 | -3.951 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.355 | 0.045 | 1.641/1.081 | 0.315 | 0.413 | 1.521/1.621 |
| $a_{12}$ | 0.178 | 0.007 | 24.338 | -1.585 | 0.051 | -31.170 |
| $b_{12}$ | 0.010 | 0.002 | 5.077 | 0.074 | 0.014 | 5.429 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.431 | 0.043 | 1.142/6.748 | 0.464 | 0.299 | 1.250/5.276 |
| $a_{32}$ | 0.212 | 0.007 | 28.404 | -1.362 | 0.046 | -29.820 |
| $b_{32}$ | -0.013 | 0.002 | -6.694 | -0.079 | 0.012 | -6.461 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.569 | 0.044 | 1.327/4.255 | 0.551 | 0.269 | 1.177/6.203 |
| $a_{13}$ | 0.127 | 0.008 | 15.783 | -2.048 | 0.074 | -27.547 |
| $b_{13}$ | 0.010 | 0.002 | 4.526 | 0.102 | 0.020 | 5.095 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.376 | 0.047 | 1.647/0.764 | 0.433 | 0.437 | 1.581/1.249 |
| $a_{33}$ | 0.499 | 0.013 | 39.557 | 0.000 | 0.052 | 0.009 |
| $b_{33}$ | -0.017 | 0.003 | -5.034 | -0.071 | 0.014 | -5.084 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.427 | 0.074 | 1.500/2.293 | 0.432 | 0.305 | 1.499/2.309 |

**Table A3: Aggregate regressions: Business Confidence**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_1$ | 0.208 | 0.014 | 15.194 | -1.431 | 0.090 | -15.904 |
| $b_1$ | 0.012 | 0.004 | 3.180 | 0.076 | 0.024 | 3.136 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.229 | 0.081 | 0.970/9.807 | 0.224 | 0.529 | 1.026/9.348 |
| $a_3$ | 0.273 | 0.019 | 14.643 | -1.066 | 0.099 | -10.764 |
| $b_3$ | -0.016 | 0.005 | -3.240 | -0.086 | 0.027 | -3.232 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.236 | 0.110 | 1.198/7.168 | 0.235 | 0.583 | 1.187/7.101 |

**Table A4: Disaggregate regressions:Business Confidence**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_{11}$ | 0.388 | 0.017 | 22.351 | -0.479 | 0.076 | -6.313 |
| $b_{11}$ | 0.011 | 0.005 | 2.357 | 0.047 | 0.020 | 2.319 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.140 | 0.102 | 1.852/0.120 | 0.137 | 0.446 | 1.834/0.179 |
| $a_{31}$ | 0.152 | 0.012 | 12.635 | -1.845 | 0.097 | -18.974 |
| $b_{31}$ | -0.008 | 0.003 | -2.516 | -0.068 | 0.026 | -2.620 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.157 | 0.071 | 1.634/1.388 | 0.168 | 0.572 | 1.666/1.100 |
| $a_{12}$ | 0.156 | 0.012 | 13.302 | -1.794 | 0.095 | -18.809 |
| $b_{12}$ | 0.006 | 0.003 | 2.000 | 0.053 | 0.026 | 2.077 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.105 | 0.069 | 1.299/4.279 | 0.113 | 0.561 | 1.319/4.260 |
| $a_{32}$ | 0.220 | 0.016 | 14.127 | -1.360 | 0.094 | -14.412 |
| $b_{32}$ | -0.011 | 0.004 | -2.542 | -0.062 | 0.025 | -2.465 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.160 | 0.091 | 1.437/3.327 | 0.152 | 0.555 | 1.451/3.077 |
| $a_{13}$ | 0.128 | 0.010 | 12.977 | -2.066 | 0.101 | -20.446 |
| $b_{13}$ | 0.007 | 0.003 | 2.654 | 0.078 | 0.027 | 2.883 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.172 | 0.058 | 1.356/4.216 | 0.196 | 0.595 | 1.386/3.987 |
| $a_{33}$ | 0.462 | 0.021 | 21.534 | -0.160 | 0.095 | -1.683 |
| $b_{33}$ | -0.011 | 0.006 | -1.869 | -0.047 | 0.026 | -1.837 |
| | $R^2$ | $\sigma$ | $DW/LM$ | $R^2$ | $\sigma$ | $DW/LM$ |
| | 0.093 | 0.126 | 1.722/0.686 | 0.090 | 0.559 | 1.745/0.594 |

# B Tables of Regression Results using Prospective Survey Data [17]

**Table B1: Aggregate regressions: Volume of output**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_1$ | 0.241 | 0.010 | 23.337 | -1.176 | 0.057 | -20.460 |
| $b_1$ | 0.019 | 0.005 | 3.660 | 0.108 | 0.029 | 3.786 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.443 | 0.059 | 1.602 | 0.447 | 0.328 | 1.106 |
| $a_1$ | 0.191 | 0.012 | 15.382 | -1.514 | 0.082 | -18.483 |
| $b_1$ | -0.026 | 0.006 | -4.235 | -0.169 | 0.041 | -4.140 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.466 | 0.071 | 0.109 | 0.500 | 0.468 | 0.438 |

[17] $R^2$ refers to the *generalised* $R^2$ for IV regressions, see Pesaran and Smith (1994). LM refers to the LM test for first order serial correlation in IV regressions, see Breusch and Godfrey (1981).

**Table B2: Disaggregate regressions: Volume of output**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_{11}$ | 0.428 | 0.010 | 43.968 | -0.293 | 0.040 | -7.288 |
| $b_{11}$ | 0.011 | 0.005 | 2.358 | 0.047 | 0.020 | 2.327 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.155 | 0.056 | 0.046 | 0.150 | 0.230 | 0.044 |
| $a_{31}$ | 0.110 | 0.007 | 15.926 | -2.170 | 0.075 | -28.756 |
| $b_{31}$ | -0.012 | 0.003 | -3.444 | -0.122 | 0.038 | -3.260 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.285 | 0.039 | 0.421 | 0.279 | 0.431 | 0.840 |
| $a_{12}$ | 0.185 | 0.008 | 23.894 | -1.508 | 0.052 | -28.951 |
| $b_{12}$ | 0.011 | 0.004 | 2.847 | 0.075 | 0.026 | 2.895 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.249 | 0.044 | 0.184 | 0.242 | 0.298 | 0.075 |
| $a_{32}$ | 0.166 | 0.009 | 18.394 | -1.677 | 0.064 | -26.382 |
| $b_{32}$ | -0.019 | 0.004 | -4.253 | -0.136 | 0.032 | -4.286 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.371 | 0.052 | 0.042 | 0.385 | 0.363 | 0.075 |
| $a_{13}$ | 0.137 | 0.012 | 11.764 | -1.919 | 0.094 | -20.330 |
| $b_{13}$ | 0.019 | 0.006 | 3.233 | 0.166 | 0.047 | 3.531 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.428 | 0.067 | 0.165 | 0.464 | 0.539 | 0.001 |
| $a_{33}$ | 0.380 | 0.016 | 24.040 | -0.506 | 0.068 | -7.418 |
| $b_{33}$ | -0.026 | 0.008 | -3.343 | -0.113 | 0.034 | -3.337 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.294 | 0.090 | 0.059 | 0.299 | 0.389 | 0.052 |

**Table B3: Aggregate regressions: Business confidence**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_1$ | 0.204 | 0.015 | 13.903 | -1.462 | 0.091 | -16.045 |
| $b_1$ | 0.021 | 0.007 | 2.924 | 0.139 | 0.045 | 3.069 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.209 | 0.084 | 2.191 | 0.207 | 0.520 | 1.365 |
| $a_3$ | 0.280 | 0.018 | 15.924 | -1.031 | 0.095 | -10.850 |
| $b_3$ | -0.030 | 0.009 | -3.437 | -0.158 | 0.047 | -3.344 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.222 | 0.100 | 0.910 | 0.218 | 0.543 | 1.167 |

**Table B4: Disaggregate regressions: Business confidence**

| | Linear probability model | | | Logit model | | |
|---|---|---|---|---|---|---|
| | estim | s.d. | t-rat | estim | s.d. | t-rat |
| $a_{11}$ | 0.384 | 0.016 | 23.477 | -0.497 | 0.071 | -7.024 |
| $b_{11}$ | 0.020 | 0.008 | 2.435 | 0.086 | 0.035 | 2.432 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.125 | 0.093 | 0.090 | 0.123 | 0.404 | 0.061 |
| $a_{31}$ | 0.155 | 0.011 | 14.011 | -1.817 | 0.094 | -19.422 |
| $b_{31}$ | -0.015 | 0.006 | -2.768 | -0.127 | 0.047 | -2.733 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.152 | 0.063 | 0.433 | 0.159 | 0.534 | 0.365 |
| $a_{12}$ | 0.154 | 0.012 | 13.235 | -1.812 | 0.092 | -19.681 |
| $b_{12}$ | 0.011 | 0.006 | 1.842 | 0.092 | 0.046 | 2.003 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.083 | 0.067 | 1.884 | 0.092 | 0.526 | 1.028 |
| $a_{32}$ | 0.223 | 0.015 | 15.401 | -1.338 | 0.088 | -15.148 |
| $b_{32}$ | -0.019 | 0.007 | -2.595 | -0.109 | 0.044 | -2.486 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.137 | 0.083 | 0.377 | 0.127 | 0.505 | 0.590 |
| $a_{13}$ | 0.125 | 0.009 | 13.387 | -2.098 | 0.096 | -21.834 |
| $b_{13}$ | 0.013 | 0.005 | 2.727 | 0.144 | 0.048 | 3.014 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.154 | 0.053 | 1.252 | 0.183 | 0.549 | 0.190 |
| $a_{33}$ | 0.466 | 0.020 | 23.845 | -0.144 | 0.085 | -1.688 |
| $b_{33}$ | -0.019 | -0.010 | -1.940 | -0.082 | 0.042 | -1.924 |
| | $R^2$ | $\sigma$ | $LM$ | $R^2$ | $\sigma$ | $LM$ |
| | 0.078 | 0.112 | 0.004 | 0.075 | 0.487 | 0.000 |

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