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Commodity risk in European dairy firms

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Abstract

We apply a multivariate mixed-data sampling (MIDAS) conditional quantile regression technique to understand the dairy commodity exposure of European dairy firms. Leveraging a theoretically sound hedonic dairy pricing framework, we show that our approach is able to identify both market and operational risk. Profit margins for butter and milk price are particularly important for operational performance. Additional tests are provided, including an application of MIDAS quantile on a period of amplified dairy market risk. Our approach thus allows dairy firms to gain new perspectives on the significant risks posed by the current structure of dairy production in Europe.

Keywords: European dairy firms, dairy commodities, mixed-data sampling, dairy markets

JEL Classification: Q14, G32

1. Introduction

The production decisions of dairy firms in Europe are increasingly driven by underlying dairy commodity prices. This move, caused by market deregulation, as well as newly globalised trading of dairy products, has introduced fresh risk to European dairy firms. In this paper, we propose a methodology to understand these risks. Our research thus addresses the under-researched area of risk in agrifirms (Cornaggia, 2013).

In little over a decade, milk production in the European Union (EU) has moved from a situation of heavy regulation that favoured stability and state intervention, to a process that favours free-market production and price-setting. Regulatory reform started in earnest in 2003 with a significant reduction in intervention prices originally put in place to guarantee minimum

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prices for dairy products, and the deregulation culminated in 2015 with the removal of production quotas, which had acted as a restraint on milk supply. These changes have posed challenges to European dairy firms as they adapt from a situation of stable supply and input and output prices, to one in which free supply and demand make dairy prices and margins highly volatile (Cechura *et al.*, 2017; Hirsch and Hartmann, 2014; Kersting, Hüttel and Odening, 2016; Läpple, Barham and Chavas, 2020). A key focus of this study is to provide a method to understand the impact this price and margin instability has on firm performance.

Against the backdrop of the above market changes that have increased the volatility of dairy commodity prices, the EU is under-served currently in respect of markets and products for risk-hedging purposes. In particular, futures markets are particularly immature, while opportunities for tailored exotic financial engineering are extremely limited. This highlights why it is important to be able to more effectively model and assess operational risk in the EU dairy firm industry. We demonstrate in this study how firms can better understand their exposure to shocks and thus potentially manage these impacts on operations internally. Thus, while our research has a different approach to the subject, it does fit with the general direction of prior research emphasising the importance of EU dairy firm flexibility in terms of both production decisions (Hirsch *et al.*, 2020) and product choice decisions (Renner, Glauben and Hockmann, 2014).

In seeking to understand the relationship between dairy prices and firm performance, we start with a hedonic dairy pricing model from Chavas and Kim (2005). This model proposes that individual dairy product price is a function of the nutritional characteristics of these products. That is, the price of a dairy product is a function of the prices of fat and protein (casein and milk serum) content, among other nutritional content. Any residual between observed prices and modelled hedonic prices is suggested to be a proxy for shocks, including innovation and competition in the marketplace. The model has previously been applied in other agricultural economic contexts, such as Gobillon, Wolff and Guillotreau (2016) who consider the same type of model for fish prices and Ortiz-Bobea (2020) for farmland asset prices. This modelling approach, therefore, provides us with a fundamental model from which we can estimate the operational shocks we seek to explain.

Our testing technique is an adapted mixed-data sampling (MIDAS) conditional quantile regression technique developed from Ghysels, Plazzi and Valkanov (2016). We apply this to model the sensitivity of European dairy transformers' operational performance as a function of dairy prices and margins. The MIDAS component (Ghysels, Santa-Clara and Valkanov, 2004; Ghysels, Santa-Clara and Valkanov, 2006) of the technique allows for the full spectrum of dairy prices and margins to be used, which are available at higher frequency (weekly and monthly) than our operational performance measures (semi-annual). Common alternatives such as Autoregressive Distributed Lag (ARDL) cointegration and Vector Autoregression (VAR) models cannot feasibly estimate in this manner. The primary advantage of being able to utilise the full range of higher-frequency input prices is that we arrive at greater precision in our quantile estimates, even over short time frames. This higher frequency provides more timely information to the dairy firm on their commodity risk exposures.

The primary contribution of our study is in demonstrating the impact of dairy prices on the performance of dairy firms. This impact has not previously been formally studied despite the important role that commodity dairy prices now play in determining market and operational risk in these firms. Despite this, there is evidence of a link between commodity price movements and firm performance for other groups of commodities (Bartram, 2005; Narayan and Sharma, 2014; Phan *et al.*, 2020). A further contribution we make is in the methodology, developing a formal misspecification test tailored to assess the adequacy of the MIDAS conditional quantile regression model, and a related model comparison test that facilitates our benchmarking exercise. This approach allows us to show empirically the conditions under which the joint use of mixed-frequency data and conditional distributional modelling are important. We also show how the MIDAS quantile (MQ) approach can be leveraged to give insights into dynamic changes over time and how to utilise MIDAS parameter estimates to perform reliable out-of-sample data tests of firm impact from dairy price movement.

In the next section, we formally present the multivariate MIDAS conditional quantile regression technique, and we develop our proposed misspecification and model comparison test. Section 3 describes the data and variables used. Section 4 provides the research findings and analysis, and Section 5 concludes the study.

2. MIDAS quantile regression modelling

We first introduce the rationale for the MIDAS conditional quantile regression modelling that we utilise in our analysis of dairy firm performance. We then discuss a model misspecification test we have developed that formally allows us to ascertain whether our MQ regression model is well-specified in explaining dairy firm performance. We also show how this misspecification test can be applied as a model comparison test to determine the relative performance of the MQ regression model compared to other popular models.

2.1. MIDAS conditional quantile regression

The lower tail distribution of a firm's cash flows is commonly used to assess the extent of operational risk associated with production processes. To effectively capture this exposure, we require a technique that explicitly allows for modelling the likelihood of these extreme downside operational outcomes. We uniquely exploit the power of targeted conditional quantile regressions to analyse this operational risk in dairy firms.

Profitability in milk transformation business depends on the margins associated with the sale of transformed products, in particular the processing of milk into butter or cheese. Another important feature of the market is the availability of prices for both input and output products, allowing us to investigate dairy transformers' operational reactions to exogenous shocks from both wholesale and retail prices (Gan, Sethi and Yan, 2005). As production managers are most averse to downside risk, our assessment of their capacity to minimise this risk relies on the left tail of the marginal distribution of the firm's operating revenue as a function of the physical dairy transformation margins. The ability of, and speed at which, a management board can manage sudden movements in the input and output markets and thus control the so-called 'chance constraint' (Charnes and Cooper, 1959; Gan, Sethi and Yan, 2005) has been extensively examined in the literature. Furthermore, this ability has been adopted to provide a comparison of firms' capacity to set up operational devices limiting downside risk and thus keep operational risk associated with their industrial activity under control (Weiss and Maher, 2009).

In this context, several advantages of quantile regression are identifiable: the ability to capture response–predictor variable dependencies that classical conditional mean regression may either fail to capture or capture quite differently; the flexibility for predictor variables to exert influence on the mean, variance and shape of the response variable distribution; and the capability to account for the heterogeneous variance that results from the complex interactions between factors that might not all be measurable or accounted for within the model (Cade and Noon, 2003). Quantile regression has been considered in the modelling of operational risk by Konstantinidi and Pope (2016). However, Konstantinidi and Pope (2016) consider only percentile time-series models with the regressors consisting of past discrete realisations of the random variable under scrutiny, or of other accounting variables with similar frequency. Furthermore, a lead–lag effect is observable for European milk observatory dairy prices when you compare the EU weighted average milk price paid to the farmers with the EU milk equivalent price based on the combination of the skimmed milk powder (SMP) and the butter prices, at a given time. This phenomenon stems from the nature of the contracts signed between milk producers and processors as the milk price paid to the farmers by the manufacturers and collected by the European milk market observatory is generally calculated based on the average combined prices of the butter and the SMP prevailing on the previous months[1].

Our contribution in this regard is to implement a method that copes with a mixed-frequency data set resulting from the combination of individual weekly and monthly exogenous market prices with accounting performance data sampled semi-annually. In this way, we get a more accurate and exhaustive insight into the operational risk dynamic augmented with the appropriate modelling of the company's cash flow sensitivity to exogenous price variables. Moreover,

1 This is graphically noticeable if you consider the dashboard published on a regular basis by the EU commission's department Directorate-General for Agriculture and Rural Development where they compare the weighted EU average price of raw milk with the EU milk equivalent price based on SMP and butter prices, available at: https://ec.europa.eu/info/sites/default/files/food-farming-fisheries/farming/documents/dashboard-dairy_en.pdf.

this MIDAS component in our statistical model effectively captures the lead–lag effect previously described by allowing for the differentiation of weights associated with the most recent prices of raw milk from those linked to SMP and butter prices.

We go further and propose a way to exploit available data optimally to meet the objective of effectively modelling extreme downside operational outcomes. This need creates a technical challenge, commonly faced in studies of commodity price influences, whereby there is a mismatch of data frequencies between variables of interest. In the context of the dairy industry, this mismatch is between dairy prices and measures of firm operational performance. In our situation, dairy prices are available at weekly frequency for milk by-products and monthly frequency for raw milk. In contrast, the accounting information on performance is published semi-annually. Addressing this data mismatch is not trivial, as price transformation functions, which either extrapolate out to the highest frequency or interpolate down to the lowest frequency, while returning a common data frequency, either lead to a loss of information or the introduction of bias. Such price transformations also typically entail assumptions about the production process, from collection to storage, associated with each company. To avoid as much as possible such limiting assumptions and to keep our model flexible, we utilise quantile regression modelling that allows for MIDAS.

We adopt, therefore, as our core model the MIDAS approach pioneered by Ghysels (Ghysels, Santa-Clara and Valkanov, 2004; Ghysels, Santa-Clara and Valkanov, 2005; Ghysels, Santa-Clara and Valkanov, 2006; Ghysels, Plazzi and Valkanov, 2016; Andreou, Ghysels and Kourtellos, 2010), which allows for mixed-data frequency series, and blend this with the quantile regression model proposed by Koenker and Bassett (1978). To this end, we first assume that the j-th quarter observation x_j of the predictor variable is the vector of higher-frequency samples $x_{\tau_{i,j}}$ within the j-th quarter, observed at the time $\tau_{i,j}$, $i = 1, \ldots, n_j$. Then we introduce a continuous weighting function $B(L^{\tau_{i,j}}; \theta)$, which offers the advantage of parsimony and tractability, through including only a limited number of hyperparameters θ into the quantile conditional regression as follows:

$$Q_{y_j}(\xi | X = x_j) = \alpha + \beta B(L^{\tau_{i,j}}; \theta) x_j + \epsilon_t$$

where on the left-hand side the ξ-th conditional quantile of y_j is regressed on the covariates x_j using a MIDAS-weighting scheme. More formally, $B(L^{\tau_{i,j}}; \theta) = \sum_{i=1}^{n_j} B(i; \theta) L^{\tau_{i,j}}$ is a finite lag operator of length n_j, applicable for quarter j, where $L^{\tau_{i,j}} x_j = x_{\tau_{i,j}}$. It follows therefore that $B\left(L^{\tau_{i,j}}; \theta\right) x_j = \sum_{i=1}^{n_j} B\left(i; \theta\right) L^{\tau_{i,j}} x_j = \sum_{i=1}^{n_j} B\left(i; \theta\right) x_{\tau_{i,j}}$. θ defines a set of hyperparameters. We discuss a particular specification of $B\left(i; \theta\right)$ below.

Several applications of the MIDAS models in mixed-frequency settings have demonstrated the interesting properties of this model (Clements and Galvão, 2009; Marcellino and Schumacher, 2010; Kuzin, Marcellino and

Schumacher, 2011; Valadkhani and Smyth, 2017; Mei *et al.*, 2020). For example, there is mitigation of the discretisation bias when higher frequency data are not available for the dependent variable. Furthermore, the MIDAS model allows to mitigate measurement error or at least to preserve more flexible and parsimonious models as mixing high frequency with low frequency instead of aggregating the highest-frequency data would amount to imposing specific restrictions on the dependant and independent variable relationships. Initially developed by Ghysels, Santa-Clara and Valkanov (2004), the essence of a MIDAS model is that any MIDAS expression can be compared under certain conditions to a state-space formulation such as the Kalman filter (Bai, Ghysels and Wright, 2013), which frequently serves as a solution for inaccurate observations modelling or to handle missing data. As this is the first application of MIDAS in agricultural finance, we apply a standard MQ model, choosing default choices such as the standard positive beta lag function for lagged data[2]:

$$B(i;\theta) = \frac{f\left(\frac{i}{n_j};\theta\right)}{\sum_{i=1}^{n_j} f\left(\frac{i}{n_j};\theta\right)}$$

with the hyperparameters vector $\theta = \{\theta_1, \theta_2\}$, where

$$f(z;\theta_1,\theta_2) \quad = \frac{z^{\theta_1-1}(1-z)^{\theta_2-1}\Gamma(\theta_1+\theta_2)}{\Gamma(\theta_1)\Gamma(\theta_2)}$$

where Γ is the standard Gamma function. This framework is readily extended to a multivariate setting.

2.2. Model misspecification test and model comparison

While there are inherent merits in using mixed-frequency data in a quantile regression model setting, as outlined in the previous section, we also formally assess the adequacy of the MQ regression model. We accordingly develop a formal misspecification test. Towards this objective, we appeal to the study of Rothe and Wied (2013), who introduce a general misspecification test that applies in the context of conditional distribution models, including quantile regression models. Our test is premised on the Cramer–von Mises measure of distance between an unrestricted *empirical* cumulative distribution function and a restricted *model derived* cumulative distribution function. We extend this misspecification test to our mixed-frequency quantile regression model setting. Appendix A provides a full technical derivation of the misspecification test we develop.

The misspecification test allows us to consider the adequacy of the mixed-frequency quantile regression on a stand-alone basis. A more complete assessment requires an appropriately designed model comparison. We leverage the misspecification test to devise a model comparison exercise that serves to highlight the importance of the respective MIDAS and quantile features of the

2 There are other parameter choices that can be made, which we leave for future studies.

MQ regression and clarifies under what conditions these combined features are relevant.

We consider the standard quantile regression and the standard MIDAS regression as benchmark models, given how the MQ regression model combines mixed-frequency data and conditional distribution modelling features in a unified model. However, direct comparison is not possible given that the quantile regression and MIDAS regression models are conditioned on different space dimensions than the MQ regression model. To address this, we marginalise the MIDAS-based joint distributions, such that we end up with a unique space dimension for all of the parametric models. That is, in the case of the high-frequency MQ regression and MIDAS regression models, it is necessary to integrate the associated high dimensional distributions in order to reduce the space dimension for the sake of comparability with the low-frequency quantile regression. The low-frequency quantile regression model can then be more fairly compared with these dimensionally reduced MIDAS regression and MQ regression models. This dimension reduction amounts to the projection from a high-dimensional model specification onto a low-dimensional space, and thus the model comparison test is considered to be conservative. Appendix A provides a technical description of our model comparison approach.

3. Data and estimation

3.1. Financial and Market Variables

The firm data set we use comprises semi-annual operational performance measures for 15 publicly-listed dairy companies in Europe from 2005 to 2018. Dairy firms are identified as firms with the Standard Industrial Classification (SIC) Code 2020 on *Compustat Global*. We exclude firms that have a dairy division but where this is not their main business.

For our analysis of operational performance, we consider measures based on prior literature (Konstantinidi and Pope, 2016; Hirsch and Hartmann, 2014; Novy-Marx, 2010). As the core operational performance measure, we calculate Operating Income (OI) scaled by assets. For robustness purposes, we also use Net Profit (NP) scaled by assets as an additional measure.

To gain a deeper market insight, we divide the firms along a couple of dimensions. First, we divide firms into small and large size based on having total assets above or below €300 million. We expect small firms to be more vulnerable to dairy market shocks due to having smaller portfolios of activities and, importantly, having lower power when it comes to negotiating with milk producers on the supply side and retailers on the demand side. Indeed, upstream and downstream marketing contracts play an important role in the distribution of bargaining power in the dairy supply chain (Borodin *et al.*, 2016; Melhim and Shumway, 2013). Second, we divide firms by Degree of Operating Leverage (DOL) as a measure of restrictions on operating flexibility.

We calculate DOL following the literature (Bhojraj *et al.*, 2020; Aboody, Levi and Weiss, 2018; Banker, Byzalov and Plehn-Dujowich, 2013; Kallapur and Eldenburg, 2005) as $1 - \beta$, where β is the slope estimate from the equation:

$$OC_i = \alpha + \beta REV_i + \epsilon_i. \tag{1}$$

OC_i is the natural logarithm of total operating costs per semi-annual period and REV_i is the natural logarithm of total revenue. The $1 - \beta$ estimate allows us to distinguish between high and low operating leverage firms, with high DOL firms being those with the most positive numbers for the measure and, therefore, cost structures that have the highest proportion of fixed to variable cost. We expect that high DOL firms will be most affected by dairy price and margin volatility due to their more limited operational flexibility. This aligns with an established literature that confirms a positive association between DOL and systematic risk (Bhojraj *et al.*, 2020; García-Feijóo and Jorgensen, 2010; Novy-Marx, 2010; Cooper, 2006; Carlson, Fisher and Giammarino, 2004).

In constructing our MQ model specification, we recognise a data availability constraint in our data set of firms. That is, that we would ideally like empirical measures of some factors that could impact operational performance, such as different levels of market power, technological innovation and government intervention, across firms. We therefore augment our model with a control variable derived from a structural model proposed by Chavas and Kim (2005). Drawing on grounded hedonic pricing theory, Chavas and Kim (2005) proposes a functional relationship between individual dairy product prices and the nutritional characteristics of these products. In particular, the price of a dairy product is deemed to be derived from the prices of fat and protein content, along with other nutritional components. This allows decomposing dairy product prices into a fundamental hedonic price component, and a non-hedonic price component that we utilise to capture the effects of unobserved market variables.

The non-hedonic price variable plays a critical role as a control variable in our setting, resolving concerns over missing variable bias and providing greater confidence in the statistical approach. As we include product margins in our main analysis and these may partly capture non-hedonic price effects (e.g. technological innovation may increase margins through production cost efficiencies), we propose a two-stage least square regression approach. We first disentangle the effect of the product margin fluctuations on the non-hedonic regressor. The derived residuals from this first-stage MQ regression are subsequently and jointly considered with cheese and butter margins in the second stage. This allows us to separate out the impact of non-hedonic components.

Dairy prices are sourced from the *EU Milk Market Observatory* and include, on the input side, monthly raw milk, and, on the output side, weekly butter and emmental cheese (as a suitable European proxy for all cheese, and henceforth just referred to as ‘cheese’) as key value-added products. For our hedonic

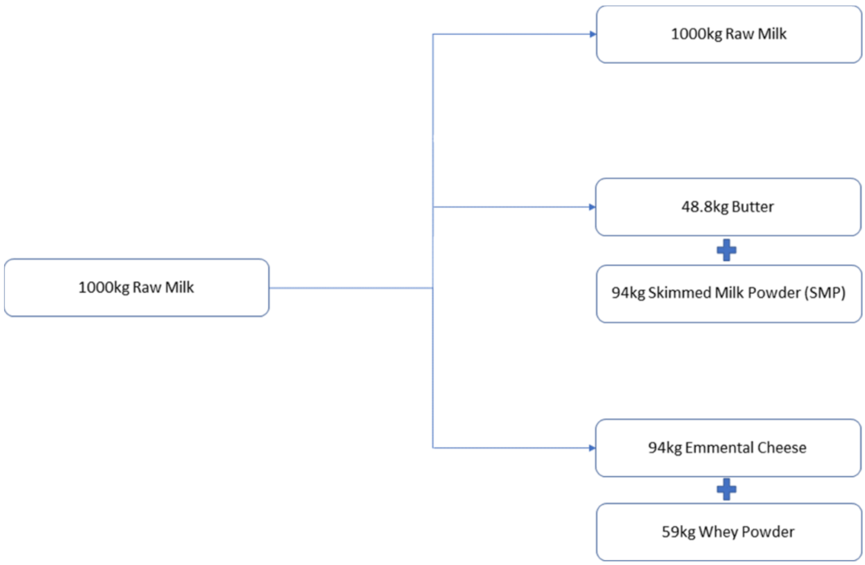


Fig. 1. Milk production and transformation choices per 1,000 kg of 4 per cent fat content raw standard milk. (i) Sell as milk, (ii) transform to butter with side product of SMP and (iii) transform to cheese with side product of whey powder. Source for transformation proportions is industry connections of the authors.

pricing analysis and margins calculation we also collect weekly SMP and whey powder prices.

As our method is a multivariate analysis of the impact of various dairy price movements on operational performance, we make a choice that the important explanatory variables are raw milk prices, and gross profitability margins for butter and cheese are determinants of operational performance. Using production ratios sourced from a large French dairy processor, we first note that processing standard milk into butter produces both butter and SMP as a by-product, leading to the following profitability ratio:

$$Butter\ margin = 48.8^{*}Butter + 94^{*}SMP - 1000^{*}Milk.$$

Cheese processing, on the other hand, produces whey powder as a by-product creating a profitability ratio:

$$Cheese\ margin = 94^{*}(Emmental)Cheese + 59^{*}Whey - 1000^{*}Milk.$$

Figure 1 shows these dairy product processing relationships. In Table 1 we provide descriptive statistics for both dairy firms and dairy prices and margins. We see from this table that large firms are more profitable and have less risk associated with that profitability than small firms. Similarly, high DOL firms are less profitable and more risky. This provides some empirical support for our decision to consider data decomposition based on size and operational

Table 1. Descriptive statistics

Panel A: Dairy firms

	OI/Assets		NP/Assets	
	Mean	Std. Dev.	Mean	Std. Dev.
All firms	0.0500	0.0400	0.0150	0.0415
Large size	0.0513	0.0203	0.0237	0.0217
Small size	0.0492	0.0492	0.0090	0.0500
Low DOL	0.0409	0.0223	0.0158	0.0253
High DOL	0.0563	0.0476	0.0144	0.0497

Panel B: Dairy products

	Mean	Std. Dev.	Skewness	Kurtosis	Minimum	Maximum
Milk price	32.21	3.79	0.05	−0.67	24.39	40.21
Butter margin	51.61	46.89	0.92	1.58	−53.36	226.20
Cheese margin	127.87	36.71	1.09	0.73	64.30	265.74

Note: Panel A provides descriptive statistics for our sample of 15 listed European dairy firms from 2005(Q4) to 2018(Q4) grouped by firm sub-category. Data sourced from *Compustat Global*. Primary dependent variables are OI scaled by assets. Secondary dependent variables are NP scaled by assets. Large/small firms defined based on having over/under €300 million total assets. DOL is the degree of operating leverage as defined in Section 3. Panel B contains descriptive statistics for milk prices and dairy margins. Raw dairy data sourced from the *EU Milk Market Observatory* for the period 01 July 2005 to 31 December 2018. Dairy margins as defined in Section 3.

leverage. Figure 2 charts the time series of the dairy margins over the sample period, with cheese appearing more stable.

3.2. Estimation approach

The main tests are multivariate MIDAS conditional quantile regressions[3,4] to determine the sensitivity of operating performance to milk prices and dairy margins. These are estimated for the 5 per cent quantiles of operational performance from 0.05 to 0.95. To conserve space, in the tables we report the set: {0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95}. Taking the example of the 0.05 quantile, this means that we examine in a multivariate analysis the impact of milk prices and dairy product margins over the relevant operational period on the fifth-lowest percentile ranked semi-annual operational performance. The full range of quantiles considered gives us a holistic, distributional assessment of operational performance.

Dairy data are incorporated into the model at weekly frequency for product margins and monthly frequency for raw milk prices. Thus, for a given semi-annual operational performance measure there are up to 26 weekly dairy data

3 We use the standard positive beta lag function in our implemented model. There are other lag choices available, including long-memory kernels. We leave these non-standard choices to future studies as the standard model appears appropriate for our context.

4 We do not consider a panel testing structure for the data as we are primarily interested in the dynamics of our group of firms as a whole, rather than individual firm-relative performances.

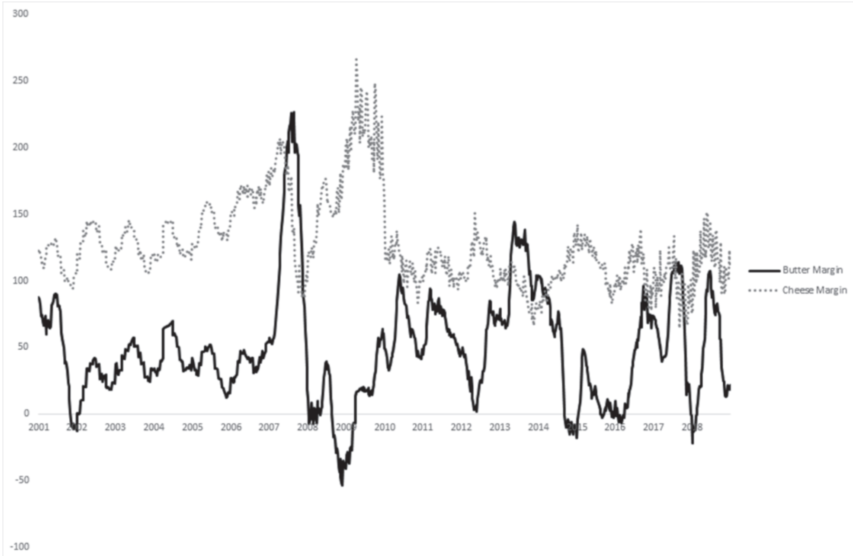


Fig. 2. Time-series plots of dairy margins. Data sourced from the *EU Milk Market Observatory* for the 01 July 2005 to 31 December 2018 period. Calculations are as outlined in Section 3 with all margins based on processing 1,000 kg of standard raw milk.

points, with the weight attached to each being determined within the model as part of the MIDAS technique as defined in Section 2. Our reported estimations are based on group average performance in a period with the groups: all firms; large- and small-size firms; and low and high DOL firms.

Following the main tests, we run a range of additional tests. First, we carry out in-sample model misspecification tests on the MQ model following the testing we develop in Section 2. We also leverage the misspecification test to benchmark the MQ model against two reasonable alternatives: a MIDAS regression model without quantiles and a quantile regression model without MIDAS. We then follow this with two further sets of robustness checks. In the first, we re-run our analysis on an alternative measure of operational performance. Specifically, NP scaled by assets is used as this alternative performance measure to determine if the results are dependent on the operational measure. In the second, we re-estimate the main tests just for the 2005Q4 to 2014Q2 period and use these trained estimates to establish the associated value for the quantile given the actual dairy prices and margins over the period of 2015–2018. We chose this time division as a number of critical operational events that happened in the 6 months following 2014Q2—the imposition of Russian sanctions on the import of EU dairy products into Russia (a large growing market for EU dairy products at the time) in September 2014 and the complete removal of EU dairy production quotas in January 2015. The Kupiec (1995) framework is used to test if the parameter estimates are consistent before and after these shocks.

4. Findings and analysis

4.1. Dairy pricing and operational performance

The main results are reported in Table 2, which gives MQ model findings for the operating performance measure of OI scaled by assets. This measure captures short-term reactivity to operational shocks through the OI numerator, comprising revenue effects, and long-term impacts through the assets denominator. Milk prices, butter margin and cheese margin are included in the multivariate model, with the beta parameters and the significance of these parameters reported. We present results by categories of grouped firms: all firms; large versus small firms; and low versus high DOL firms.

We further investigate the magnitude of influence of dairy prices and margins. Figure 3 contains subplots of the in-sample sensitivity of a one standard deviation positive shock of any dairy price or margin, on firm operational performance. In these charts the black solid line shows the initial (non-shocked) operational performance across each 5 per cent quantile. We then observe how this moves subsequent to a given dairy price or product margin shock. The greater the magnitude of movement away from the initial position, the greater the operational performance impact.

Overall, we identify some important relationships between dairy prices and margins and operational performance, suggesting the value of the MQ approach. For our initial all-firms analysis we find that milk prices generally have a negative impact across the operational performance distribution, while product margins have a positive impact. The butter margin has a stronger positive effect than the cheese margin. We find, however, that the most interesting findings are at the between-firm level.

For example, it can be seen that high DOL firms are far more exposed to dairy risk than low DOL firms. Given the high levels of fixed costs relative to variable costs for such firms, increases in milk prices can be seen to have a greater detrimental impact on operational performance. On the flip side, for the same reason, high DOL firms are well positioned to exploit increases in product margins. This sensitivity aligns with our earlier expectation that high DOL firms have much more limited operational flexibility to respond to dairy market volatility. Indeed, DOL is seen as a determinant of systematic risk, measuring as it does a firm's reliance on fixed costs García-Feijóo and Jorgensen (2010). So our finding aligns with an established observation in the literature that high DOL firms have high systematic risk and are often associated with high book-to-market ratios and, hence, a value premium (Carlson, Fisher and Giammarino, 2004; García-Feijóo and Jorgensen, 2010; Bhojraj *et al.*, 2020).

In a similar manner to high DOL, we find that small firms are more exposed to dairy market movements than large firms. Indeed, we see a very similar pattern in terms of economic significance across the operational performance distribution for small and large firms when compared, respectively, to high DOL and low DOL firms. This is somewhat unsurprising as many of the high DOL firms are also classified as small firms. This suggests additional reasons

Table 2. MQ model: sensitivity of operational performance to dairy prices and margins

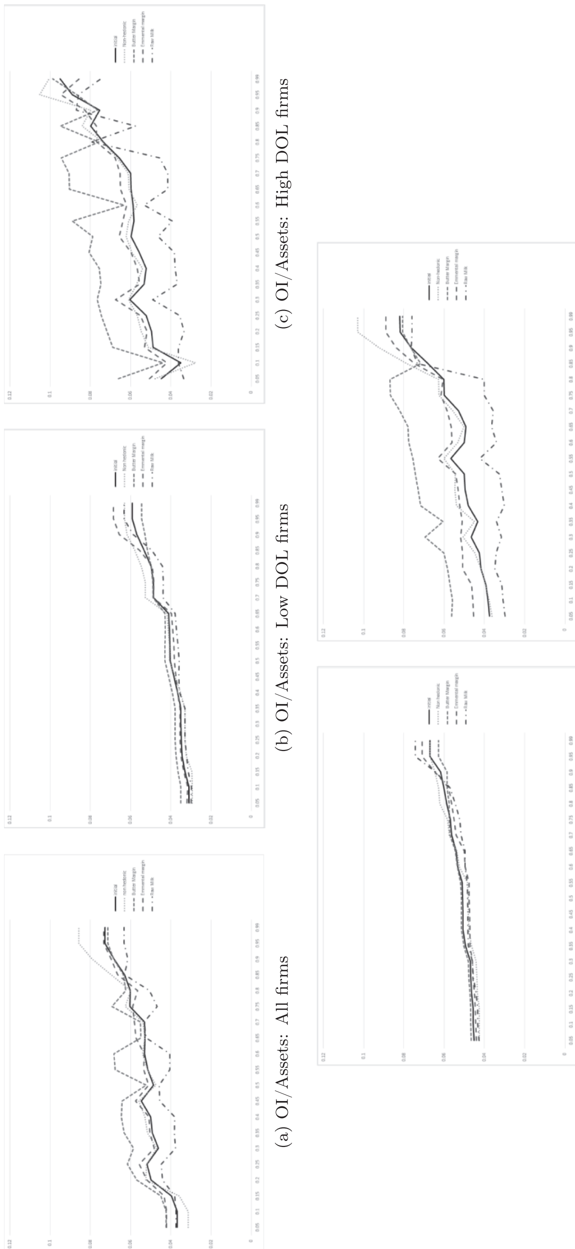
	OI/Assets						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
All firms							
Milk	0.0002***	0.0002**	−0.0020***	−0.0008**	−0.0039***	−0.0020***	−0.0027***
Butter	0.0001***	0.0001***	0.0002***	0.0001*	0.0002***	0.0000	0.0000
Cheese	0.0002***	0.0002***	0.0001***	0.0001	0.0000	0.0000	0.0000
Non-Hedonic	−0.0006***	−0.0006***	0.0000	−0.0001	0.0002*	0.0011***	0.0013***
Large-size firms							
Milk	−0.0007***	−0.0006***	−0.0004*	−0.0006***	−0.0013***	0.0007***	0.0021***
Butter	0.0000***	0.0000**	0.0000	0.0000	0.0000	−0.0001**	−0.0001***
Cheese	0.0000***	0.0000***	0.0000	−0.0001***	−0.0001**	0.0001***	0.0001***
Non-Hedonic	−0.0003***	−0.0003***	−0.0003***	−0.0003**	0.0002	0.0003	0.0000
Small-size firms							
Milk	−0.0022***	−0.0021***	−0.0024***	−0.0050***	−0.0057***	0.0000	−0.0017***
Butter	0.0004***	0.0004***	0.0004***	0.0006***	0.0006***	0.0000	0.0000
Cheese	0.0002***	0.0002***	0.0003***	0.0001***	0.0000	0.0002***	0.0002***
Non-Hedonic	−0.0001***	0.0000	0.0002*	0.0004**	0.0003	0.0016***	0.0021***

(continued)

Table 2. (Continued)

	OI/Assets						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Low DOL firms							
Milk	−0.0003***	−0.0003***	−0.0005***	−0.0013***	−0.0014***	0.0005***	0.0012***
Butter	0.0001***	0.0001***	0.0001***	0.0001*	0.0000	−0.0001***	−0.0001***
Cheese	0.0000***	0.0000	0.0000	−0.0001**	0.0000	0.0003***	0.0003***
Non-Hedonic	−0.0002**	−0.0002*	−0.0002	0.0000	0.0004*	0.0005***	0.0004**
High DOL firms							
Milk	−0.0032***	0.0004***	−0.0047***	−0.0038***	−0.0058***	0.0033***	−0.0009***
Butter	0.0005***	0.0002***	0.0005***	0.0004***	0.0007***	0.0000	−0.0001
Cheese	0.0002***	0.0002***	0.0001***	0.0002***	0.0001	0.0002***	0.0002***
Non-Hedonic	0.0003**	−0.0007***	0.0005**	0.0002	0.0001	0.0005	0.0016***

Note: Results from MIDAS conditional quantile regression of OI scaled by assets to milk prices and processing margins (2005–2018). The β parameters from the MIDAS Quantile model are reported. All variables as defined in Section 3; milk: raw milk price; butter: butter margin; cheese: emmental cheese margin. The non-Hedonic variable of Chavas and Kim (2005) is as derived in Section 3.
*$p<0.10$,
**$p<0.05$,
***$p<0.01$.



(a) OI/Assets: All firms

(b) OI/Assets: Low DOL firms

(c) OI/Assets: High DOL firms

(d) OI/Assets: Large size firms

(e) OI/Assets: Small size firms

Fig. 3. MIDAS Quantile model: Quantile operational performance (i.e. OIs scaled by assets) sensitivity to a one standard deviation positive shock to dairy price or margin.

for the impact we demonstrate. Firstly, large firms are more likely to have better channels through which to manage dairy market risk, particularly through more diverse portfolios of activities and more sophisticated use of market risk strategies. Secondly, large firms have much greater negotiating powers on both the supply side and demand side. Small firms, on the other hand, are at a competitive disadvantage in this respect. The dairy supply chain is characterised by upstream operators (milk producers) and downstream operators (retailers) who exert, through marketing contracts, both price- and quantity-based pressure on dairy transformers. In such a context, it is probably just the largest dairy companies who can cope with the growing bargaining power of retailers (Borodin *et al.*, 2016). Loy *et al.* (2015) discuss how prices adjust for dairy products in retailers as a result of these European dynamics.

4.2. Model misspecification and model comparison

The previous section underscores our argument for the use of the MIDAS Quantile model to better understand the operational performance distribution. Now we more formally examine the specification of the MIDAS Quantile model, ideally with benchmarking against alternative model specifications. We perform model misspecification tests for the MIDAS Quantile regressions across all firms and sub-groups of firms. We also report comparisons with reasonable alternative models; namely, a MIDAS model without quantiles and a quantile regression model without MIDAS. These results support the strength of the MIDAS Quantile approach.

Looking first at the misspecification results in Table 3, which are reported for OI scaled by assets, we see the findings of the test developed in Section 2. This is an in-sample verification of the multivariate joint distribution of the test of high-frequency dairy data and low-frequency performance data. The scores for the MIDAS quantile model are comfortably above the 5 per cent significance level for all groups of firms, suggesting the model has strong in-sample specification.

When we examine the model comparisons tests, we make some observations. The first observation is that there is a large drop in p-values for the MIDAS Quantile in the model comparison tests for all firm categories. As noted in Section 2 the model comparison method imposes a limitation on the MIDAS Quantile, in that in order to allow comparability with the lower-frequency quantile model, the method marginalises the effect of using high-frequency dairy prices and margins, which is a core strength of the MIDAS Quantile approach. This imposed limitation explains the drop in p-values for certain categories and shows the importance of the MIDAS component in explaining operational performance.

A second observation is made when comparing the MIDAS Quantile, albeit in reduced form, with the separate MIDAS and quantile regressions. We see evidence that aligns with our observations from the previous section. The MIDAS Quantile model can be seen to be well specified for all groups. Secondly, while the alternative MIDAS and quantile models are also deemed well

Table 3. MIDAS Quantile model: Model misspecification test and model comparison

	All	Large	Small	Low DOL	High DOL
OI/Assets					
Misspecification	0.735	0.775	0.715	0.69	0.645
Model comparison:					
MIDAS Quantile	0.29	0.225	0.3	0.32	0.14
MIDAS	0.1	0.535	0.145	0.26	0.04
Quantile	0.275	0.32	0.06	0.355	0.05

Note: Reports *p*-value associated with the MIDAS Quantile misspecification test as developed in Section 2. The table also reports *p*-values from model comparison tests following Rothe and Wied (2013) with alternative models of MIDAS and Quantile regressions. Three comparative models are included: (1) a MIDAS Quantile model, except without lagged values; (2) a MIDAS model, estimated on mean values rather than quantiles; (3) a Quantile model, without MIDAS weighting of dairy prices and margins.

specified for large and low DOL firms, this is not the case for small and high DOL firms. Indeed, the quantile model can be seen to be misspecified for small and high DOL, while the MIDAS model is misspecified for high DOL firms. Even in its reduced form, the MIDAS Quantile offers a superior specification.

4.3. Dynamics analysis

We now focus on the dynamics of the dairy firms' business operations. We primarily examine the profitability as a function of the DOL. Our analysis, in contrast to Section 4.1 which examined the tail quantile performances, now takes the median performance and examines the dynamics of this performance. To do so, we consider as a proxy of conditional expected profitability, the weekly estimated conditional median throughout this analysis and compute the standardised difference between the high and low operating leverage companies. This provides us with a dynamic representation of expected performance difference among these two sets of companies over time.

This dynamic study reinforces our results in Section 4.1 by showing that sensitivity to dairy product pricing (we rely on butter production and its by-product, SMP) is different for high DOL companies relative to low DOL companies. Figure 4 indeed shows that in environments with high SMP and butter prices, and hence high revenues, the high DOL companies tend to outperform the low DOL companies. This dynamic is observed in the context that the relative weight of the fixed costs (for example large productive investment expenses) is proportionally less important for high DOL companies, hence a better profitability. This aligns with our previous claim that the risk profile of high DOL companies is directly linked to the butter margin.

Another core finding is that the way dairy by-products evolve relative to each other also plays an important role in these firms' relative performance. Following the recent decoupling between SMP and butter prices (cf. upper panel of Figure 5) it is interesting to differentiate two types of high-revenue environment. First, and as observed before 2017, we see that both SMP and butter prices spike up simultaneously, following a low production of milk or

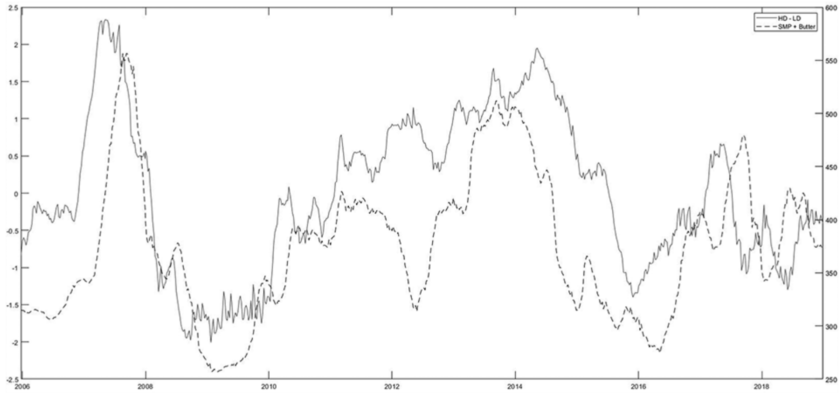


Fig. 4. DOL spread and butter products prices

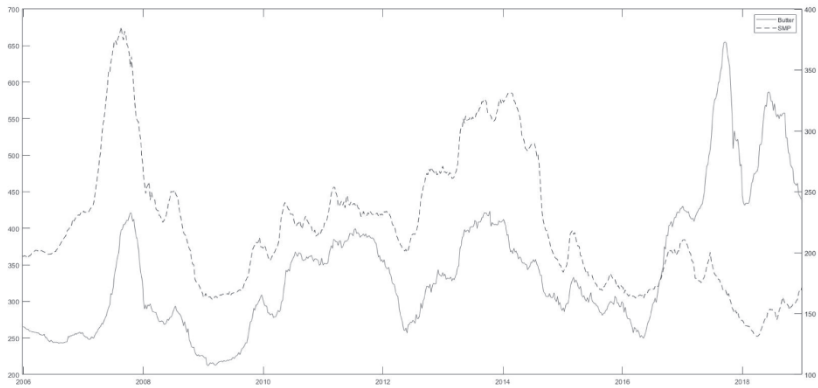
a positive shock on demands for both by-products. However, in the second scenario, the high milk equivalent price environment is characterised by a decoupled evolution of the two by-products, such as recently observed with historically high butter prices since 2017 driven by strong demand which has implicitly led to a larger production of SMP without demand to absorb it, providing downward pressure on SMP prices. To represent these two environments we computed the price difference between butter and SMP, respecting the proportion of by-product we obtained from 1,000 kg of raw milk. The lower panel of Figure 5 compares this price difference with the high DOL versus low DOL median performance spread and shows that high DOL companies tend to underperform when SMP depreciates relative to butter as the firms have potentially less leeway to adjust their cost of production. Inversely, when the SMP appreciates relative to butter, companies with high operating leverage outperform and suffer less from the fixed cost burden.

We suggest that these findings could have important implications for policymakers deliberating European dairy market supports. Measures such as milk price floors or production quotas tend to favour high DOL over low DOL companies and could potentially motivate companies to increase their operating leverage, for instance by investing in fixed assets. The same outcome should be expected with public interventions directly sustaining the price of the SMP. On the contrary, any support from the European Commission for the butter price will be of greater benefit to low DOL companies.

4.4. Additional robustness tests

To support our main analysis, we run two further sets of robustness checks. The first set of checks involves changing the performance measure to a reasonable alternative. NP is chosen as an appropriate alternative to OI. The results for NP normalised by assets are reported in Table 4, while the magnitude of influence of dairy prices and margins on this performance measure are investigated

(a) Historical butter and SMP weekly prices



(b) DOL spread and Butter-SMP spread

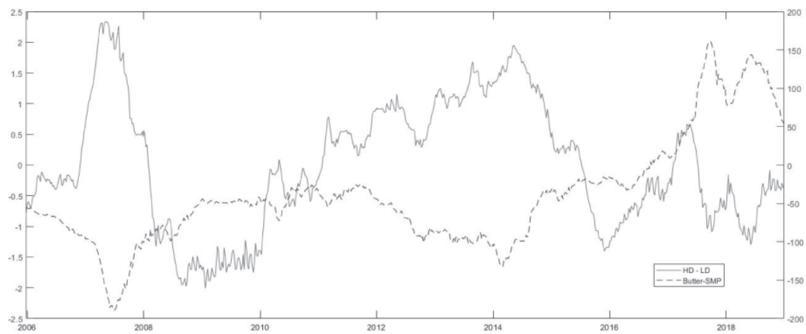


Fig. 5. DOL spread and butter products spreads

in Figure 6. There is little notable change in direction in these results compared to the main results. We generally find again a negative impact of milk on performance, while the products margins have a positive impact. For small firms and high DOL firms, the magnitudes of the effects are more pronounced. These observations are made again across the profitability performance distribution underscoring the importance of the quantile component of the MIDAS Quantile model.

Our second set of robustness tests is reported in Table 5 and involves estimating parameters for dairy price and margin sensitivity over an in-sample period of 2005Q4 to 2014Q2. We then determine if these estimates hold up over an out-of-sample period of 2015Q1 to 2018Q4. The reason for this separation is that in the period 2014Q3 to 2015Q1 two significant operational events for dairy firms occurred. Firstly, the banning of EU dairy imports into Russia in September 2014, and secondly, the full lifting of dairy quotas in January

Table 4. MIDAS Quantile model: sensitivity of operational performance to dairy prices and margins

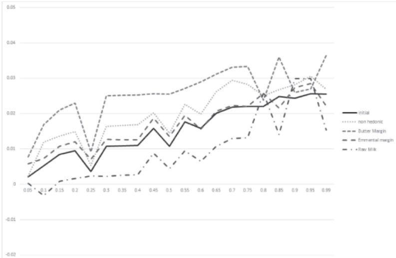
	NP/Assets						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
All firms							
Milk	−0.0005***	−0.0024***	−0.0004***	−0.0018***	−0.0025***	0.0016***	0.0012***
Butter	0.0001***	0.0003***	0.0001***	0.0003***	0.0003***	0.0000	0.0000
Cheese	0.0001***	0.0001***	0.0001***	0.0001**	0.0000***	0.0001***	0.0001***
Non-Hedonic	0.0000	0.0007***	0.0002	0.0004**	0.0006***	0.0004*	0.0005***
Large-size firms							
Milk	−0.0010***	−0.0010***	−0.0011***	−0.0015***	−0.0005**	0.0004	0.0018***
Butter	0.0000	0.0000	0.0000	0.0001***	0.0000	0.0000	0.0000
Cheese	−0.0001***	−0.0001***	0.0000***	0.0000	0.0000	0.0000	0.0000
Non-Hedonic	0.0005***	0.0004***	0.0003***	0.0004***	0.0003*	0.0001	0.0005*
Small-size firms							
Milk	−0.0032***	−0.0030***	−0.0025***	−0.0025***	−0.001	−0.0054***	−0.0055***
Butter	0.0005***	0.0005***	0.0004***	0.0003***	0.0001	0.0005***	0.0004***
Cheese	0.0001***	0.0001***	0.0002***	0.0001***	0.0000	−0.0002***	−0.0002***
Non-Hedonic	0.0008***	0.0007***	0.0005***	0.0005***	0.0001	0.0004**	0.0004***

(continued)

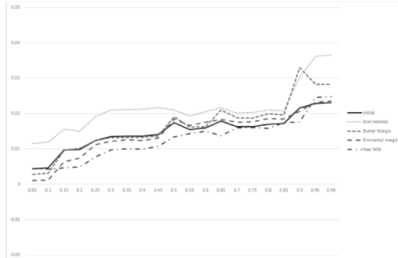
Table 4. (Continued)

	NP/Assets						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Low DOL firms							
Milk	0.0000	−0.0001*	−0.0013***	−0.0012***	−0.0001	−0.0011***	0.0005***
Butter	0.0000***	0.0000*	0.0000	0.0000	0.0001*	0.0003***	0.0001***
Cheese	−0.0001***	−0.0001***	0.0000	0.0000	0.0000	0.0000*	0.0000
Non-Hedonic	0.0007***	0.0007***	0.0007***	0.0004***	0.0004***	0.0009***	0.0013***
High DOL firms							
Milk	−0.0038***	−0.0038***	−0.0028***	−0.0016***	−0.0050***	0.0028***	0.0018***
Butter	0.0005***	0.0005***	0.0004***	0.0006***	0.0005***	0.0000	0.0000
Cheese	0.0001***	0.0001***	0.0001***	0.0003***	−0.0001*	0.0002***	0.0002***
Non-Hedonic	0.0008***	0.0008***	0.0005***	−0.0001	0.0002	0.0005	0.0007***

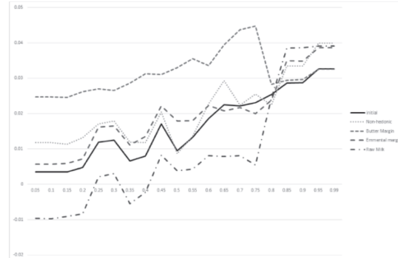
Note: Results from MIDAS conditional quantile regression of NP scaled by assets to milk prices and processing margins (2005–2018). The β parameters from the MIDAS Quantile model are reported. All variables as defined in Section 3; milk: raw milk price; butter: butter margin; cheese: emmental cheese margin. The non-Hedonic variable of Chavas and Kim (2005) is as derived in Section 3.
*$p < 0.10$,
**$p < 0.05$,
***$p < 0.01$.



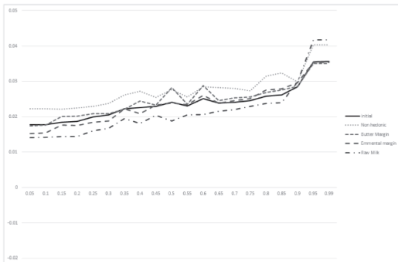
(a) NP/Assets: All firms



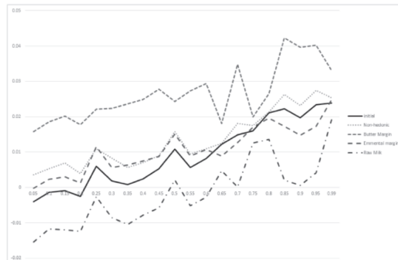
(b) NP/Assets: Low DOL firms



(c) NP/Assets: High DOL firms



(d) NP/Assets: Large size firms



(e) NP/Assets: Small size firms

Fig. 6. MIDAS Quantile model: quantile operational performance (i.e. NP scaled by assets) sensitivity to one standard deviation positive shock to dairy price or margin.

Table 5. MIDAS Quantile model: Kupiec tests of parameter stability

	0.05	0.10	0.25	0.50	0.75	0.90	0.95
OI/Assets							
All	0	0	1	1	0	1	1
Large size	0	1	1	1	1	1	0
Small size	1	0	1	1	1	1	1
Low DOL	1	1	1	1	1	1	0
High DOL	0	0	1	0	1	1	1

Note: The Kupiec (1995) framework is used to test the use of MIDAS conditional quantile regression parameters estimated during the 2005Q4 to 2014Q2 period, in modelling the sensitivity of OI scaled by assets to milk prices and processing margins, during the 2015Q1 to 2018Q4 period. '1' indicates significant parameter stability at the 5 per cent level. MIDAS Quantile model as per Table 2.

2015. Until 2014, Russia had been a major export destination for European dairy firms, and while the quota lifting had been clearly signalled in advance of its implementation, it still represented a significant change in supply dynamics for the dairy market.

Our testing approach involves Kupiec (1995) tests of the 5 per cent quantile parameters of operating performance estimated during the pre-sanctions period. In our results, parameters that show significance at the 5 per cent level are denoted as 1, with other parameters denoted as 0. A 0 indicates that the pre-event period trained parameters do not effectively estimate the actual operating performance during the post-event period. The findings in Table 5 show decent parameter stability even during this extreme period. The dynamics of operational performance parameters, as measured by OI/assets, remains generally consistent. There are a few breaks in parameter stability on the downside, but upside performance parameters are generally significantly consistent. These findings therefore show reasonably consistent parameter estimates from the MIDAS Quantile model even during an extreme period of operational volatility.

5. Implications and conclusions

In this study we have shown, for the first time, a direct connection between dairy prices and margins and the operational performance of European dairy firms. This connection means that operational performance, right across the distribution, is influenced by dairy market factors. Firms appear to be ineffective in managing this risk, especially small companies with high operating leverage. We show the advantages of a MIDAS Quantile technique that allows for extracting information from the weekly and monthly prices of dairy products compared to semi-annual operational performance measures. Parameter estimates based on MIDAS Quantile also have intertemporal consistency, even in times of operational stress, as illustrated by our successful use of 2005–2014 estimates for the 2015–2018 period. This was a period with significant changes in the industry with the imposition of Russian dairy import sanctions and the lifting of dairy production quotas.

The MIDAS method therefore has strong benefits as a tool for dairy firms, enabling them to understand their dairy commodity exposures and manage these risks in a timely manner. More generally, the technique highlights that European dairy firms are exposed to dairy product risks that can be managed. We find this to be pronounced for small firms that lack, in particular, the negotiating power that large firms can exert on both the demand and supply sides of the value chain. It would be worth exploring whether these risks are acceptable or whether these risks should be operationally or financially hedged. The strong exposure of small dairy transformers, in particular, to movements in the margins for butter are an example of this risk. Butter margins can be partially hedged through futures on SMP and whole milk powder, but there is little habit of doing so in Europe due to the prices of dairy products being historically stable. Yet, the financialisation of dairy commodities and the deregulation of the European dairy market has created price instability that should be addressed and managed and is unlikely to become anything other than more significant over time, especially with new and upcoming EU free trade agreements with major dairy exporters, such as New Zealand and Canada. The global prices of dairy by-products and increased protectionism also introduce risk due to the ability of global shocks to reflect back on performance. This was illustrated by the imposition of Russian sanctions preventing dairy exports to Russia that has impacted on European dairy producers since 2014.

We further show that operating leverage (DOL) matters for dairy firms in Europe. Firms with a high DOL, signifying lower operational flexibility, are vulnerable to the impact of dairy prices and margins. Such firms are more exposed to the negative impacts of milk prices, while their fixed-variable cost structure can benefit from the widening of product margins. Consideration could be given to adjusting such cost structures to better suit the new reality of volatile underlying prices. This highlights the importance of both looking at a MIDAS weighting of input prices and also of examining quantile performance. A major finding of this study is the variation of influence across quantiles.

There are some limitations to this study, the first of which is that we mainly study a small subset of European dairy firms; those that are listed on a stock market. A more detailed examination of further dairy firms would allow for a wider understanding of the extent of operational exposure of the broader set of dairy firms to dairy commodity risk, although data constraints are an issue. We also do not have much public information on the extent to which European dairy firms are using flexible contracting with suppliers and consumers to manage these risks, and that would be useful to understand in order to gauge how firms are starting to manage this new set of market and operational risks. Related to this, more direct information on specific firm impacts of shocks and innovations in the industry would be useful for firm-specific modelling.

A last issue that would be pertinent to understand is whether the newly developed European dairy commodity futures market can offer sufficient depth and liquidity to financially hedge dairy risk. The use of such hedging is becoming common in other major dairy markets such as the USA and New Zealand, but European dairy futures are very much in their infancy and might need to develop substantially to meet the demands of a newly volatile European dairy industry. Notwithstanding these limitations, we suggest that our study provides a practical and rigorous framework for understanding the impact of dairy prices on the performance and risks of dairy firms.

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Appendix A Technical appendix

A.1. Model misspecification test

Towards a test statistic for the misspecification test, we consider the distance between the empirical joint distribution $\widehat{H}$ and the estimator $\widehat{H}^0$ calculated by integrating the conditional cumulative distribution obtained through the MIDAS quantile regression $\widehat{F}$ ($\widehat{f}$ denoting the associated density) with respect to the marginal distribution $G(x)$ (g denoting the associated density) of the explanatory random variable X. To account for the full set of high-frequency observations within the MIDAS quantile regression model, we integrate the conditional distribution with respect to the weekly covariate observations $X_{\tau_{i,t}}$, $i = 1, \dots, m$, within the t-th semi-annual period. Appealing to the chain rule, the joint density may be decomposed into the following product of conditional densities:

$$H^0(y, x_{\tau_{1:m}}) = \int_0^{x_{\tau_1}} \cdots \int_0^{x_{\tau_m}} \int_0^y h(\omega, \zeta_m, \dots, \zeta_1) d\omega\, d\zeta_m \dots d\zeta_1 \tag{A1}$$

$$= \int_0^{x_{\tau_1}} \cdots \int_0^{x_{\tau_m}} \int_0^y f(\omega|\zeta_m, \dots, \zeta_1) g_{m|m-1:1}(\zeta_m|\zeta_{m-1}, \dots, \zeta_1) \dots g(\zeta_1) d\omega\, d\zeta_m \dots d\zeta_1 \tag{A2}$$

where, for example, the notation $g_{m|m-1:1}$ is introduced to define the conditional probability distribution of x_{τ_m} given the high-frequency explanatory variables observed within a given semi-annual period $x_{\tau_{1:m-1}} = x_{\tau_1}, \dots, x_{\tau_{m-1}}$. Defining $\mathbb{1}\{\cdot\}$ to be the indicator function, we can then write the joint cumulative distribution as:

$$H^0(y, x_{\tau_{1:m}}) = \int \cdots \int F(y|\zeta_m, \dots, \zeta_1) \mathbb{1}\{\zeta_m \le x_{\tau_m}\} \dots \mathbb{1}\{\zeta_1 \le x_{\tau_1}\} g_{m|m-1:1}(\zeta_m|\zeta_{m-1}, \dots, \zeta_1) \dots g(\zeta_1)\, d\zeta_m \dots d\zeta_1.$$

This can then be discretised for the weekly covariate observations $X_{\tau_{i,t}}$, $i = 1,\ldots,m$ within each of $t = 1,\ldots,n$ semi-annual periods, to give:[5]

$$H^0(y, x_{\tau_{1:m}}) = \sum_{t_m=1}^{n} \cdots \sum_{t_1=1}^{n} F(y|X_{\tau_{m,t_m}},\ldots,X_{\tau_{1,t_1}})\mathbb{1}\{X_{\tau_{m,t_m}} \le x_{\tau_m}\}\ldots\mathbb{1}\{X_{\tau_{1,t_1}} \le x_{\tau_1}\}$$
$$g_{m|m-1:1}(X_{\tau_{m,t_m}}|X_{\tau_{m-1,t_{m-1}}},\ldots,X_{\tau_{1,t_1}})\ldots g(X_{\tau_{1,t_1}}).$$

Note that to distinguish the layered summations, we subscript the semi-annual period index t with a weekly index j such that $t_j = 1,\ldots,n$ refers to week j in each of the semi-annual periods. If we denote $X_{\tau_{1:m,t}} = X_{\tau_{1,t}},\ldots,X_{\tau_{m,t}}$ and assume that the observations are not time independent, we can demonstrate, for instance for the first conditional density above, that $g_{m|m-1:1}(X_{\tau_{m,t_m}}|X_{\tau_{m-1,t_{m-1}}},\ldots,X_{\tau_{1,t_1}})$ equals 1 when $t_1 = \cdots = t_m$, i.e. when the sequence is as observed within a given semi-annual period, and 0 otherwise. This follows from the fact that it is only on one occasion in our sample, i.e. for semi-annual period t, that we obtain the value $X_{\tau_{m,t}}$ given the sequence of high-frequency data $X_{\tau_{m-1,t}},\ldots,X_{\tau_{1,t}}$. This same logic follows for the subsequent conditional probabilities.

We thus obtain the estimates of the joint distribution $\widehat{H}_n^0$:

$$\widehat{H}_n^0(y, x_{\tau_{1:m}}) = \frac{\sum_{t=1}^{n} \widehat{F}(y|X_{\tau_{m,t}},\ldots,X_{\tau_{1,t}})\mathbb{1}\{X_{\tau_{m,t}} \le x_{\tau_m}\}\ldots\mathbb{1}\{X_{\tau_{1,t}} \le x_{\tau_1}\}}{n} \tag{A5}$$

where we subscript H with n to emphasise the dependency on the number of semi-annual periods, and the estimated conditional cumulative density $\widehat{F}(y|X_{\tau_{1:m,t}})$ can be expressed as the integration of the quantile regression function using a change of variable:

$$\widehat{F}(y|X_{\tau_{1:m,t}};\widehat{\mathbf{\Theta}}) = \int_0^1 \mathbb{1}\{\widehat{\alpha}(u) + \widehat{\beta}(u)\sum_{i=1}^{m} B(i;\widehat{\theta}(u))X_{\tau_{i,t}} \le y\}\, du \tag{A6}$$

where we let $\widehat{\Theta}_u = \{\widehat{\alpha}(u), \widehat{\beta}(u), \widehat{\theta}(u)\}$ be the set of hyperparameters estimated for each u-quantile regression with u defined over $[0,1]$, such that $\widehat{\mathbf{\Theta}} = (\widehat{\Theta}_u)_{u\in[0,1]}$, and where we retain the positive beta lag function $B(i;\theta)$ as suggested by Ghysels, Santa-Clara and

5 Given the observations $(\mathbf{X}_i)_{i=1,\ldots,n}$ of a d-dimensional random vector $\mathbf{X} = (X_1,\ldots,X_d) \in \mathbb{R}^d$ with a joint distribution μ, the k-element empirical marginal distribution function $F_n^k(x)$ based on the observations $\mathbf{X}_i = (X_{1i},\ldots,X_{di})$ is provided by:

$$F_n^k(x) = \frac{1}{n}\text{card}\{i \le n : X_{ki} \le x\}$$
$$= \frac{\sum_{i=1}^{n} \mathbb{1}\{X_{ki} \le x\}}{n} \tag{A3}$$

while the empirical joint distribution $F_n(\mathbf{x})$ of $\mathbf{x} \in \mathbb{R}^d$ is defined as:

$$F_n(\mathbf{x}) = \frac{1}{n}\text{card}\{i \le n : \mathbf{X}_i \le \mathbf{x}\}$$
$$= \frac{\sum_{i=1}^{n} \mathbb{1}\{X_{1i} \le x\}\ldots\mathbb{1}\{X_{di} \le x\}}{n}. \tag{A4}$$

Valkanov (2006). Moreover, $\widehat{H}_n^0(y, x_{\tau_{1:m}})$ verifies the asymptotic properties defining a joint cumulative distribution:

$$\lim_{y, x_{\tau_{1:m}} \to \infty} \widehat{H}_n^0(y, x_{\tau_{1:m}}) = 1, \qquad \lim_{y, x_{\tau_{1:m}} \to -\infty} \widehat{H}_n^0(y, x_{\tau_{1:m}}) = 0. \tag{A7}$$

With the model-derived cumulative distribution function established, we now build the empirical cumulative distribution function through the following summation:

$$\widehat{H}_n(y, x_{\tau_{1:m}}) = \frac{\sum_{t=1}^{n} \mathbb{1}\{Y_t \le y\} \mathbb{1}\{X_{\tau_{m,t}} \le x_{\tau_m}\} \ldots \mathbb{1}\{X_{\tau_{1,t}} \le x_{\tau_1}\}}{n}. \tag{A8}$$

Finally, with these definitions in place, we can now define the quantile regression adapted test statistics T_n underlying our misspecification test. Aligning with the Cramer–von Mises concept of distributional distance, this test statistic is given by:

$$\begin{aligned} T_n &= n \int \left(\widehat{H}_n^0(y, x_{\tau_{1:m}}) - \widehat{H}_n(y, x_{\tau_{1:m}}) \right)^2 d\widehat{H}_n(y, x_{\tau_{1:m}}) \\ &= \sum_{t=1}^{n} \left(\widehat{H}_n^0(Y_t, X_{\tau_{1:m,t}}) - \widehat{H}_n(Y_t, X_{\tau_{1:m,t}}) \right)^2. \end{aligned} \tag{A9}$$

A.2. Model comparison

Comparing the results of the misspecification test as applied to the MIDAS quantile regression, with the analogous results of the misspecification test as applied to the quantile regression, and the dimensionally reduced MIDAS regression and MIDAS quantile regression models, provides some important insights.

The misspecification test offers interesting advantages provided that we can assess, for each model, a distance based on the same density of the probability measure $\widehat{H}_n(y, x)$, without making any assumption about the original data-generating processes. The distances measured between the empirical joint distribution and any parametric model implied that multivariate probability distribution are comparable as long as the same marginal joint distribution can be estimated through each parametric model. We proceed with the technical details pertaining to the dimensional reduction required around the MIDAS quantile regression and MIDAS regression models.

We begin with the MQ regression. The associated joint distribution is defined as:

$$\begin{aligned} H_{MQ}^0(y, x_{\tau_{1:m}}) = \int_0^{x_{\tau_1}} \cdots \int_0^{x_{\tau_m}} \int_0^{y} & f(\omega | \zeta_m, \ldots, \zeta_1) g_{m|m-1:1}(\zeta_m | \zeta_{m-1}, \ldots, \zeta_1) \\ & \ldots g(\zeta_1) d\omega \, d\zeta_m \ldots d\zeta_1. \end{aligned}$$

We can shrink this expression to a low-dimensional joint distribution by marginalising the high-frequency components of the MQ joint distribution:

$$\begin{aligned}
H^0_{MQ}(y,x) &= \int_0^y \int_0^x f(\omega,\zeta_m) d\zeta_m \, d\omega \\
&= \int_0^y \int_0^x \int \cdots \int f(\omega|\zeta_m,\ldots,\zeta_1) g_{m|m-1:1}(\zeta_m|\zeta_{m-1},\ldots,\zeta_1) \\
&\qquad \ldots g(\zeta_1)\, d\zeta_1 \ldots d\zeta_{m-1}\, d\zeta_m \, d\omega \qquad \text{(A10)} \\
&= \int_0^{y_t} \int_0^{x_t} \sum_{t_1=1}^{n} \cdots \sum_{t_{m-1}=1}^{n} f(\omega|\zeta_m, X_{\tau_{m-1,t_{m-1}}},\ldots,X_{\tau_{1,t_1}}) \\
&\qquad g_{m|m-1:1}(\zeta_m|X_{\tau_{m-1,t_{m-1}}},\ldots,X_{\tau_{1,t_1}}) \ldots g(X_{\tau_{1,t_1}}) d\zeta_m \, d\omega \\
&= \sum_{t_1=1}^{n} \cdots \sum_{t_m=1}^{n} \widehat{F}_{MQ}(y|X_{\tau_{m,t_m}},\ldots,X_{\tau_{1,t_1}};\widehat{\boldsymbol{\Theta}}_{MQ}) g_{m|m-1:1}(X_{\tau_{m,t_m}}|X_{\tau_{m-1,t_{m-1}}},\ldots,X_{\tau_{1,t_1}}) \\
&\qquad \ldots g(X_{\tau_{m,t_m}}) \mathbb{1}\{X_{\tau_{m,t_m}} \leq x\} \\
&= \frac{\sum_{t=1}^{n} \widehat{F}_{MQ}(y|X_{\tau_{m,t}},\ldots,X_{\tau_{1,t}};\widehat{\boldsymbol{\Theta}}_{MQ}) \mathbb{1}\{X_{\tau_{m,t}} \leq x\}}{n}
\end{aligned}$$

where $\widehat{F}_{MQ}(y|X_{\tau_{m,t}},\ldots,X_{\tau_{1,t}};\widehat{\boldsymbol{\Theta}}_{MQ})$ is the MQ-based conditional cumulative distribution, and the final result follows from our observation in the previous section that the conditional densities are equal to 1 when the sequence is as observed within a given semi-annual period, and 0 otherwise.

We can do similarly for the MIDAS (M) regression model. We follow the same steps and marginalisation technique, which leads to the following expression:

$$\begin{aligned}
H^0_{M}(y,x) &= \int_0^y \int_0^x \int \cdots \int f(\omega|\zeta_m,\ldots,\zeta_1) g_{m|m-1:1}(\zeta_m|\zeta_{m-1},\ldots,\zeta_1) \\
&\qquad \ldots g(\zeta_1)\, d\zeta_1 \ldots d\zeta_{m-1}\, d\zeta_m \, d\omega \qquad \text{(A11)} \\
&= \frac{\sum_{t=1}^{n} \widehat{F}_{M}(y|X_{\tau_{m,t}},\ldots,X_{\tau_{1,t}};\widehat{\boldsymbol{\Theta}}_{M}) \mathbb{1}\{X_{\tau_{m,t}} \leq x\}}{n}
\end{aligned}$$

where the conditional density amounts to the properly shifted distribution retained for the innovation term, which in our case is assumed to be Gaussian. Accordingly, we can write the expression of the conditional cumulative distribution as:

$$\widehat{F}_{M}(y|X_{\tau_{m,t}},\ldots,X_{\tau_{1,t}};\widehat{\boldsymbol{\Theta}}_{M}) = \int_0^y \phi(\omega;\widehat{\mu}_M,\widehat{\sigma}_M)\, d\omega$$

where ϕ is the normal density with (i) mean

$$\widehat{\mu}_M = \mathbb{E}[y|X_{\tau_{m,t}},\ldots,X_{\tau_{1,t}}] = \widehat{\alpha}_M + \widehat{\beta}_M \sum_{i=1}^{m} B(i;\theta_M) X_{\tau_{i,t}}$$

where $B(i;\theta_M)$ corresponds to the beta lag function and (ii) standard deviation $\widehat{\sigma}_M$ associated with the white noise of our MIDAS model, estimated using the overall data sample.

In the case of the quantile (Q) regression model, we are of course already working with a low-dimensional joint distribution ${H_Q}^0(y,x)$, associated with the quantile-regression-based conditional distribution $\widehat{F}_Q$ (with associated density $\widehat{f}_Q$) such that:

$$\begin{aligned} H_Q^0(y,x) &= \int_0^y \int_0^x \widehat{f}_Q(\omega|t_0)g(t_0)dt_0\, d\omega \\ &= \frac{\sum_{t=1}^n \widehat{F}_Q(y|X_t, \widehat{\mathbf{\Theta}}_Q)\mathbb{1}\{X_t \le x\}}{n} \end{aligned}$$

where

$$\widehat{F}_Q(y|x, \widehat{\mathbf{\Theta}}_Q) = \int_0^1 \mathbb{1}\{\alpha_Q(u) + \beta_Q(u)x \le y\}\, du.$$

We can then compute the statistic T_n associated with each of these models using the dimensionally reduced version of (A9), while the critical values are estimated for each model following the same bootstrap method as in Rothe and Wied (2013). We can compare the standardised performances of the models through the resulting p-values from the misspecification test. This allows us to ascertain the performance of the dimensionally reduced MIDAS quantile regression model relative to the dimensionally reduced MIDAS regression and the standard quantile regression models. More insight is gained, however, by means of comparing these p-values with the corresponding p-value from the misspecification test applied to the full MIDAS quantile regression model. When the p-values are both above the Rothe and Wied (2013) 5 per cent significance level and are comparable in terms of magnitude, this suggests that there may not be much merit to extending to the more complex MIDAS quantile regression specification. On the other hand, when the p-value of the MIDAS quantile regression is higher, this suggests that joint MIDAS and quantile modelling is important.