CEJOR
DOI 10.1007/s10100-017-0477-8

ORIGINAL PAPER

Should business rely on business cycle forecasting?

Tobias F. Rötheli[1]

Abstract We investigate the circumstances in which business cycle forecasting is beneficial for business by addressing both the short-run and the long-run aspects. For an assessment of short-run forecasting we make a distinction between using publicly available information of cycle probabilities and the use of resources to sharpen this outlook. A sharpened forecast can pay off because it helps the firm to optimally select its output mix. For a long-run perspective we show that firms whose optimal level of operation varies with varying selling prices gain from an accurate assessment of the likelihood of the states of expansion and recession. Petroleum refining in the U.S. is econometrically studied as an exemplary industry. The results document cyclical regularities that indicate that forecasting is advantageous for firms in this industry.

Keywords Forecasting · Business cycle · Planning · Strategic management

JEL Classification E32 · E37 · M21 · L21

1 Introduction

Firms have been using business cycle forecasts as well as producing their own forecasts for a long time and have considered forecasting to be a key element of successful business practice (Rötheli 2007; Friedman 2014). The last two decades of the nine-

---

I would like to thank Christoph Mölleken, James Juniper, Lukas Rosenberger, Walter von Siebenthal, Martin Watts and participants in a seminar at the University of Newcastle for comments. The detailed comments by an anonymous referee were particularly helpful.

✉ Tobias F. Rötheli
tobias.roetheli@uni-erfurt.de

1 Department of Economics, University of Erfurt, Nordhäuser Straße 63, 99089 Erfurt, Germany

Published online: 22 May 2017

teenth century up until the 1920s can be considered an early peak of business cycle forecasting and of its popularity among producers. The great depression which had not been forecast and which lasted much longer than experts had foreseen diminished the role of forecasting for roughly two decades. The 1950s and 1960s saw a strong revival of business cycle forecasting (Luedicke 1954; Lewis 1959). Ethe (1956) by the means of case studies and Wheelwright and Makridakis (1973) by way of a survey of leading managers provide insights on applications of forecasting methods in business practice. The enthusiasm of business for forecasting general economic activity has not suffered from skeptical findings of empirical economists regarding the predictability of the course of the economy (Zarnowitz 1992; Diebold and Rudebusch 1999). In fact, a majority of writers addressing the business decision maker (e.g., Turner 1978; Hudson 1993; Achuthan and Banerji 2004; Ellis 2005) suggest using a modern econometric version of practices that have been known since the early years of business forecasting. Authors like Giliand (2010)—who sees forecasting as largely a waste of resources—are clearly in the minority.

This paper offers an analysis of the circumstances in which firms can profit from relying on business cycle forecasting. One way forecasting can generate an advantage is when a sharpened outlook helps to optimize the short-run product portfolio of a firm. A longer-term effect is the gain a producer can realize when he/she chooses the size of his/her operation on an accurate estimate of the likelihood of expansions and contractions. Section 2 leads into the analysis by presenting a Markov perspective of the business cycle. Section 3 describes the conditions that make spending resources on a (limited) increase in predictive accuracy of a forecast worthwhile. Section 4 looks at how characteristics of the business cycle can influence the optimal choice of a firm's size of operations and what probabilities should guide this strategic decision. Section 5 offers an empirical application. The econometric analysis of selling prices from the petroleum refining industry suggests that this industry is likely to benefit from both short- and long-run assessments of business cycle frequencies.

2 A suggestion of conceptualization

In order to discuss the potential benefits of business cycle forecasting we build on a modern probabilistic view of the cycle. The starting point is the notion of a dating of business cycle conditions as exemplified by the National Bureau of Economic Research (NBER). This institution publishes calendar dates regarding peaks and troughs of U.S. business cycle expansions and contractions. Figure 1 documents such a display of the cycle with 1s marking quarters of expansion and 0s quarters of contraction.[1] The next step is to assume that the business cycle can be described as a Markov process. This means that we take the switching probabilities as only being a function of the present state of the economy. Hence, good times follow good times with a given probability and bad times follow good times with one minus this probability. More concretely, in good times (expansion of real GDP) there is a probability of a continuation of good

[1] With this choice we take the perspective that the stage of the cycle is objectively, if at times only with a lag, identifiable.

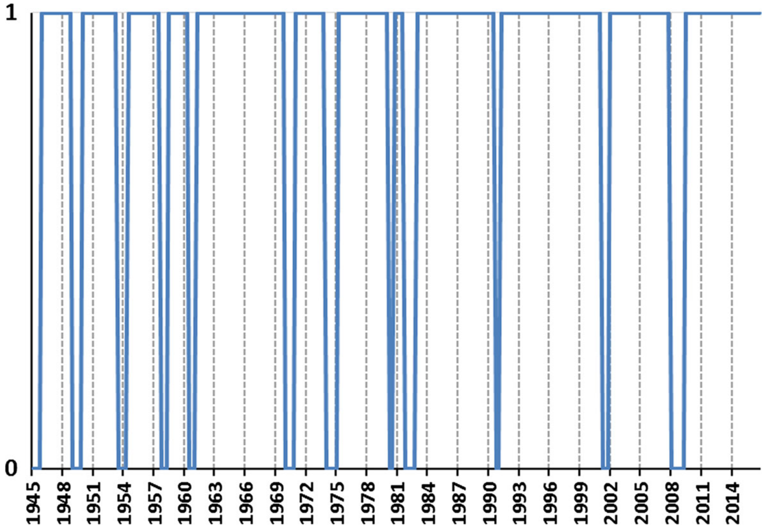

Fig. 1 Booms (1) and recessions (0) according to NBER dating

times—call it p—and correspondingly a probability $1 - p$ that good times will come to an end in the next period (i.e., next quarter). In qualitatively the same manner but with different probabilities the same applies in recessions: in bad times (contraction of real GDP) there is a probability of a continuation of bad times—call it q—and a probability of $1 - q$ of a return to good times.

Empirically, drawing on quarterly data of the U.S. business cycle since 1945 and until the end of 2016 these probabilities are of the order of $p = 0.95$ and $q = 0.73$ (updated from Rötheli 2012). One implication of this Markovian view of the business cycles is that expansions do not tend to die of old age (Diebold and Rudebusch 1990; Zarnowitz 1992).[2] Furthermore, and of key importance for the purpose of forecasting, this perspective suggests the practical impossibility of precisely predicting turning points. The arrival of a recession, e.g., is a calculable risk but trying to see it coming is like trying to look around the corner. The first issue to be clarified in the next section addresses the short-term issue of optimizing the portfolio of produced goods with the benefit of an informed business cycle forecast.

3 Variations of optimal output mix over the business cycle

Business cycle econometricians of recent years have investigated whether additional (and what kind of) information is able to sharpen the business cycle outlook (Estrella and Mishkin 1998; Sephton 2009; Batchelor 2009; Harding and Pagan 2010; Liu and Moench 2014). That is, can we find data which besides the current stage of the cycle help to predict whether the economy is continuing as before or whether we

[2] Note that a dependence on duration would not invalidate the analysis that follows but would merely make the probability p depend on the length of the expansion.

are at a turning point? The presumption of our analysis here is that such information potentially exists.[3] In the figure of speech used before there exists information and (forecasting) technology that lets us see just a bit more of what is behind the corner. One concrete form in which such a sharpening of the business cycle outlook is beneficial is the situation where the spread of prices across the different goods a firm produces is affected by the state of the business cycle.[4] In this case the output mix will be influenced by the business cycle forecast because for most businesses changing the output mix takes some time.

In the following we ask under what conditions it makes sense to use resources in trying to forecast whether a boom continues or comes to an end.[5] To answer this question we have to model the payoffs for the firm under different business cycle conditions. For this purpose we need to specify the economic details of prices and costs. Concretely, we think of the firm as producing two different goods. The first of these goods (labeled L, for large) yields a relatively higher selling price in times of expansion compared to times of contraction while the price of the second good (S, for small) is relatively higher in recession times. Very likely (and a point to which we will return in the next section) prices of both goods will be lower during contractions than during expansions. An example for the described variation of prices would be the prices and profit margins for cars of different size and fuel-efficiency: during recessions the demand for larger cars tends to decrease more strongly than for smaller cars and vice versa during expansions (see Morris 1996; OECD 2009). This tendency is reflected in the cyclicality of prices.[6]

We will not address issues of oligopolistic price setting here and instead take selling prices to be exogenous for the firm and denote them as P_L^B, P_S^B, P_L^R, and P_S^R with the subscript indicating the type of good and the superscript indicating the state of the macroeconomy. Consider further that the firm faces rising marginal costs in the production of either good. This is captured in the following cost function for the firm

$$C\left(Q_S, Q_L\right) = \alpha + \beta\left(Q_S^2 + Q_L^2\right), \tag{1}$$

[3] Finding one or more variables that help explain the probabilities of a continuation of the present state (and the probability of a turning point) is only one requirement for making an informed forecast. A further requirement is to find a quantitative relationship that is stable and hence reliable for out-of-sample forecasting. The results documented in Estrella and Mishkin (1998) indicate that stock price data and interest rate spreads are the potentially most informative variables for improving probability assessments for the U.S. business cycle. Information concerning these variables are not only significant for explaining the cycle in-sample but also predict out-of-sample.

[4] One could think of other aspects relevant for decision making (not to be modeled here) where this type of analysis would apply. Besides the varying output prices the costs of inputs may also be affected by the business cycle.

[5] Clearly, the question of forecasting during recessions could be developed as a straightforward extension of the present analysis.

[6] An early contribution to the sensitivity of prices to cyclical changes is from Wasson (1953) who documents sizable variations across types of durable goods. See also Gordon (1990) for a major contribution to the measurement of prices of durable goods. Effective selling prices, e.g. for automobiles, have to incorporate rebates which, particularly during recessions, can be significant and furthermore prices tend to decline as customers in recessions tend to relocate purchases to low-priced retailers (see Coibion et al. 2015).

where β is positive.[7] For simplicity we take a resource constraint for the firm which limits the sum of the total of all produced goods according to $Q_S + Q_L = 1$. Maximizing expected profits leads to the following outputs for S- and L-goods, respectively[8]:

$$Q_S = \frac{1}{2} - \frac{p}{4\beta}\left(P_L^B - P_S^B\right) - \frac{1-p}{4\beta}\left(P_L^R - P_S^R\right) \tag{2}$$

$$Q_L = \frac{1}{2} + \frac{p}{4\beta}\left(P_L^B - P_S^B\right) + \frac{1-p}{4\beta}\left(P_L^R - P_S^R\right) \tag{3}$$

The result in terms of output will typically be a deviation from a fifty-fifty (i.e., 1/2) split in the production of the two goods and instead an outcome with $Q_L > Q_S$. Even if the size of the price differences under different cyclical conditions (i.e., $P_L^B - P_S^B > 0$ and $P_L^R - P_S^R < 0$) were of similar absolute size the outcome would be $Q_L > Q_S$.[9] Hence, in expansion times output of L-goods will typically be higher than output of S-goods. Intuition on the benefits of business cycle forecasting can be further developed when, for simplicity, we assume that $P_L^B = \bar{P} + \delta$, $P_S^B = \bar{P} - \delta$, $P_L^R = \underline{P} - \delta$, and $P_S^R = \underline{P} + \delta$ where $\bar{P}$ is the average price of the firm's products in boom times and $\underline{P}$ in recession times, and δ is a parameter indicating the cyclical effect on the spread of prices.[10] In this case the expression for the expected profit $E(\Pi)$ during good times simplifies to

$$E(\Pi) = p\bar{P} + (1-p)\underline{P} - \alpha - \frac{\beta}{2} + \frac{\delta^2}{2\beta}(2p-1)^2 \tag{4}$$

It becomes clear that the expected profit rises as the probability p deviates farther from the value of 1/2. This effect is the larger the more the spread of prices (i.e., the term δ) is affected by the business cycle.

Next, we ask whether business cycle forecasting over just relying on the historical frequency of a continued expansion is profitable. The following setup helps to analytically assess this question. We see an informed forecast as giving firms a more differentiated view regarding the probability of a continuation of a boom. More specifically, with business cycle forecasting there are equal probabilities (of 0.5) of, (1) a situation type A emerging in which the informed forecast indicates that the probability of a continuing boom is more likely than based on a simple Markov view (i.e., higher

7 We could differentiate the parameter β over types of goods but for the basic insights developed here this is not material.

8 Expected profit, given $Q_S + Q_L = 1$, can be written as $E(\Pi) = p\left[Q_L P_L^B + (1-Q_L) P_S^B\right] + (1-p)\left[Q_L P_L^R + (1-Q_L) P_S^R\right] - \alpha - \beta Q_L^2 - \beta(1-Q_L)^2$. Maximizing expected profit rather than strategies like, e.g., downside risk control (Barro and Canestrelli 2014) is the appropriate criterion here given the repetitive nature of the decision problem and the availability of probability estimates.

9 Given $p = 0.95$, $P_S^R - P_L^R$ would need to be 19 times higher than $P_L^B - P_S^B$ to neutralize the described effect of business cycle expectations on the output mix.

10 With the labels concerning goods chosen as "large" and "small" the situation of a typical firm will be that δ is positive. However, for our analysis these labels could be changed in any way (e.g., good 1 and good 2) and δ could also be negative.

than p) and, (2) a situation type B where the reverse holds. To be specific, the first case is described by an informed probability of continued good times of $p + \phi$ and the second case by a probability of continued good times of $p - \phi$. Obviously, the parameter ϕ is the measure of the quality of the forecast.[11] When the production decision is made based on the informed forecast we denote the resulting expected profit by $E_F(\Pi)$. It turns out that the difference between expected profits with and without forecasting can be expressed as

$$E_F(\Pi) - E(\Pi) = \frac{2\delta^2\phi^2}{\beta}. \tag{5}$$

Hence, we find that relying on a forecast that sharpens the producer's probability assessment tends to increase expected profit and observe that this gain rises with the square of the parameter ϕ, that is, with the quality of the forecast. Further, the gain from an informed forecast is larger the more the cycle affects the spread of prices across goods. Last, note that neither the general level of prices (i.e., $\bar{P}$ and $\underline{P}$) nor their variation over the cycle (i.e., $\bar{P} - \underline{P}$) affects the benefit derived from short-term forecasting.

Thus, industries in which the spread of prices across the spectrum of produced goods is more affected by the cycle will tend to benefit more from business cycle forecasts.[12] This perspective can also help to explain differences in the prevalence of business cycle forecasting in different industries. Consider also changes in the precision of business cycle forecasts (in our model changes in ϕ) over time and we can see some of the reasons for the variations in the popularity of business cycle forecasting over time.

4 Size of operation and business cycle frequencies

In this section we describe a further, strategic, way in which a firm can benefit from relying on business cycle estimates. The point developed here has so far not received

[11] This probabilistic perspective on the role of forecasting can intuitively be grasped when we consider forecasting as selecting a ball from an urn. In the case of the *uninformed* forecast we can think of nature (or fate) as drawing a ball every quarter during the expansion from an urn with 100 balls where 95 balls have the label "expansion" and 5 balls are labeled "contraction". This makes for a probability of 0.95 in favor of a continued expansion. Think now of forecasting as affording a glimpse into the urn and perceiving that nature is drawing from one of two smaller urns termed A and B with 50 balls each and with unequal numbers of balls labeled recession. Consider as an illustration the case where urn A contains two recession balls and urn B contains three of them (implying 48 expansion balls in A and 47 such balls in B). This means that with informed forecasting we are either in the situation with $p = 0.96$ or $p = 0.94$. In terms of the terminology introduced this is a situation with a $\phi = 0.01$. Accordingly, an informed business cycle forecast allows us a sharper assessment of the likelihood of a continuation of a boom. If we know the choice to be from an A type situation we know with a higher probability that the expansion continues. By contrast, in a B type situation we know that a continuation of the expansion has a lower probability. Hence, the role of the forecaster is to tell management whether they face situation A or B. In the former case an informed forecast makes us—and rationally so—more optimistic regarding the expansion and in the latter it makes us more pessimistic. Clearly, if ϕ is zero we are back in the non-informed situation. Also, ϕ has an upper boundary of $1 - p$.

[12] Obviously, the potential benefit of an informed forecast has to be weighed against the costs of the forecast. See Rötheli (1998) for an elaboration of this point.

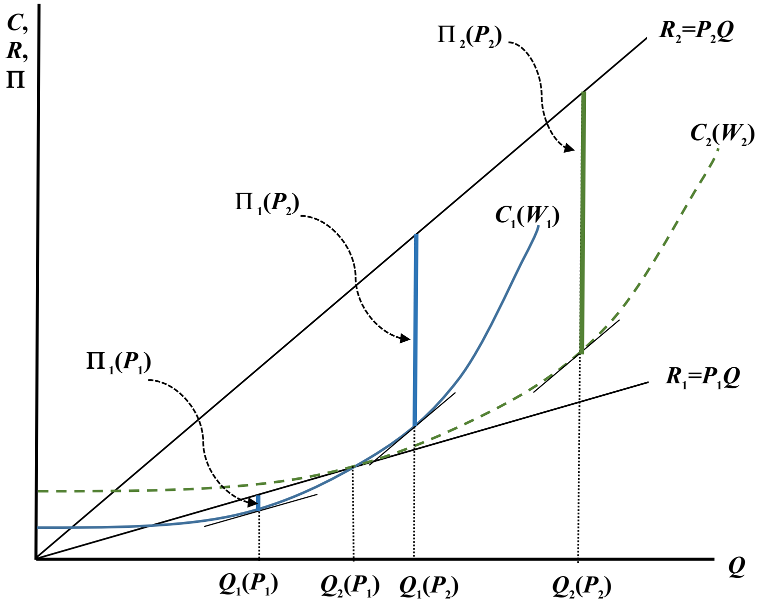

Fig. 2 Selling price, size of operation and profit

much attention in the literature. It concerns the question of how business cycle frequencies should be taken into account when making long-term capacity choices. Given investments in fixed capital a firm cannot easily adjust its size over the cycle even if, under different conditions, different sizes of operations would be profit optimal. We study the limiting case when as regards size the firm has no flexibility over the cycle and hence must make a choice that fits both boom times and recession times. The Markovian perspective outlined above also implies that there is an unconditional probability that the economy is in expansion (ε) and, similarly, an unconditional probability of contraction $(1-\varepsilon)$. Empirical estimates of these probabilities for the post WW2 era are 0.85 and 0.15, respectively.[13]

Here, we focus on the choice of a firm regarding the size of its operation and the level of invested capital. Producers typically face the tradeoff between an operation that demands relatively little capital but involves costs that rise relatively quickly as production increases and an alternative with more capital invested that goes with a lesser increase in costs. This choice depends on the anticipated selling prices and the relative likelihood of expansion and contraction times. As a concrete example, consider the situation of a firm having to choose a level of invested wealth (W) considering that at a lower (higher) level of W the costs of financing are lower (higher) but average costs are higher (lower). Figure 2 shows two cost functions that represent the choices.

$C_1\ (W_1)$ represents costs at a lower level of invested wealth and $C_2\ (W_2)$ show costs at a higher level of invested wealth $W_2 > W_1$. In both cases we see costs as a function of the quantity of goods produced and sold (Q). Revenue (R) is proportional to Q

[13] The transition probabilities discussed before and (unconditional) probabilities of the two states of a Markov process are related by the equation $\varepsilon = (1-q)\,/\,(2-p-q)$.

with the selling price as the factor of proportionality. Hence, R_1 and R_2 represent revenues given two different prices with $P_2 > P_1$. Let us first focus on the firm with the cost function $C_1(W_1)$. When the price is at P_1 the firm chooses quantity $Q_1(P_1)$ and realizes profits of $\Pi_1(P_1)$ which can be seen in the graph as the vertical solid line. At the higher price P_2 the same firm chooses the higher output $Q_1(P_2)$ and realizes profits of $\Pi_1(P_2)$. Turning now to the firm with the higher invested wealth we see that at the lower price P_1 this firm produces at $Q_2(P_1)$ and with its revenues can just cover costs (i.e., realizes a level of zero profits). Given the higher price P_2 the larger firm now chooses the output $Q_2(P_2)$ and realizes profits of $\Pi_2(P_2)$. What becomes apparent from this graphical display is that the choice between the two levels of possible operation depends on the level of the selling price.

Evidently, if the selling price were known always to be at P_1 then the firm would opt for the smaller operation whereas at the higher price P_2 the firm would choose the larger operation. Returning to the reality of the business cycle the firm faces uncertainty and thus has to assess the likelihood of different levels of its selling price. The analysis presented in graph 2 already allows to see that the choice of firm size becomes a question of probabilities of price outcomes. With a high probability of the low price being realized the firm would opt for the smaller size. However, as the probability of the higher price being realized increases the firm will tend to choose the larger size of operations. To make explicit the connection with the business cycle we see P_1 and P_2 (call them $\underline{P}$ and $\bar{P}$) as the prices realized during recession and expansion, respectively. Hence, to set the optimal size of the operation the firm needs an accurate estimate of the likelihood of being in expansions and recessions. As already indicated at the beginning of this section accurate estimates of the relative frequencies are 0.85 and 0.15, respectively. For a fuller understanding we need to make the analysis just sketched more general. Here, the optimal size of the firm's operation can take many different values instead of just the two values shown in Fig. 2. Specifically, we propose using a cost function of the form[14]

$$C = \rho W + \frac{\beta}{W^{0.5}} Q^2. \tag{6}$$

The parameter ρ indicates the interest rate to be paid on invested wealth (W) and β is a cost parameter. Clearly, higher invested wealth increases fixed (and average) costs on the one hand but decreases variable costs on the other. With this general formulation the problem to be solved is one of finding the optimal level of invested wealth. Maximizing expected profits leads to the optimal size of invested wealth according to[15]:

$$W = \left[\frac{\varepsilon \bar{P}^2 + (1-\varepsilon)\,\underline{P}^2}{8\beta\rho}\right]^2 \tag{7}$$

Equation (7) clarifies the strategic importance of scaling the wealth invested according to an accurate estimate of the likelihood of expansion times.

[14] This cost function has already proved helpful in the modeling of industrial concentrations processes (Rötheli 2008).

[15] The problem to be solved is $\mathrm{Max}_{\bar{Q},\underline{Q},W}\, E(\Pi) = \varepsilon\left[\overline{PQ} - \rho W - \frac{\beta}{W^{0.5}}\bar{Q}^2\right] + (1-\varepsilon)\left[\underline{PQ} - \rho W - \frac{\beta}{W^{0.5}}\underline{Q}^2\right]$.

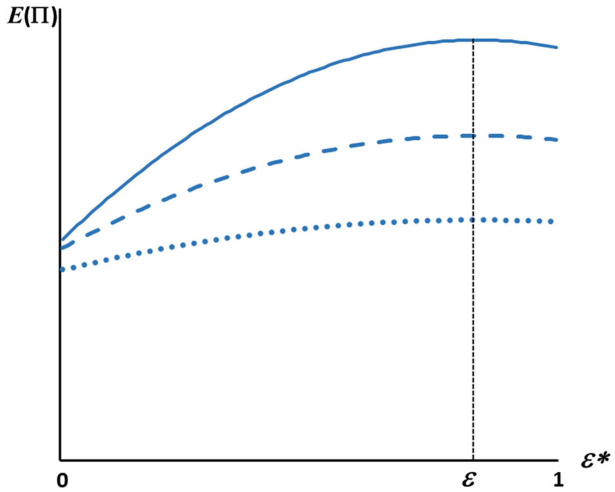

Fig. 3 Expected profit and subjective probability of expansion

When using the term ε for the objective and accurate estimate of this probability and ε^* the (possibly biased) subjective estimate of this probability we can clarify how a biased assessment hurts the firm. Figure 3 shows how expected profit varies with the subjective probability of the decision maker. The three lines for expected profit stand for three possible differences between $\bar{P}$ and $\underline{P}$ over the business cycle. The solid line stands for expected profit with the largest price difference and the dotted line for the smallest price difference. Independently of the price difference the maximum of the profit function is reached when the subjective expectation of the decision maker coincides with the objective expectation, i.e., when $\varepsilon^* = \varepsilon$. If W is chosen by an overly optimistic outlook regarding the relative frequency of good times (with $\varepsilon^* > \varepsilon$) the firm will chose too large a level of invested wealth while too pessimistic an assessment will result in a level of W that is too small. In both cases expected profit is reduced.

5 An empirical example

Here, we provide empirical evidence relating to the theoretical analysis offered. We will document for one industry for which the relevant data are available (1) that selling prices vary significantly over the cycle and (2) that the price spread across the production portfolio is also affected by the cycle. Finding (1) suggests that the firms in this industry tend to profit from an accurate assessment of long-run business cycle frequencies while finding (2) indicates that this industry also tends to benefit from sharpened, more accurate, short-run forecasts of the cycle.

For an empirical study of this kind it would greatly help to have the selling prices of products (or product lines) for individual firms over time. In particular, we would need time series stretching back over several business cycles. Unfortunately, such data is extremely hard to come by. Hence, we limit our analysis to one particular industry. We chose the U.S. petroleum refinery industry because it is probably the only industry for which the price data from the Bureau of Labor Statistics on industrial producer prices (PCU-code 32411) coincides with the selling prices of a representative firm in this industry.[16] Moreover, the assumption of perfect competition made in the analysis accords well with the functioning of markets for refinery products. In particular, besides the price index for the whole industry we have sub-indexes for the following product groups:

(1) Regular gasoline (PCU-324110324110121)
(2) Premium gasoline (PCU-324110324110123)
(3) Jet fuel (PCU-3241103241104Y)
(4) Kerosene, except jet fuel (PCU-3241103241107Y)
(5) Home heating oil and other distillates (PCU-324110324110AY1)
(6) Diesel fuel (PCU-324110324110AY2)
(7) Heavy fuel oils (PCU-324110324110DY)
(8) Liquefied refinery gases (PCU324110324110R)

Here we leave out products for which the time series of prices does not reach back as far as the 1980s (e.g. we exclude mid-premium gasoline). In the following we report results of estimating the following type of time-series regression

$$ln\left(P_{i,t}\right) = \gamma_0 + \gamma_1 ln\left(P_t^{OIL}\right) + \gamma_2 ln\left(Y_t\right). \tag{8}$$

In this estimation P_i is the price of good (or group of goods) i while P^{OIL} stands for the price of crude oil which is the dominant cost variable in this industry. Real U.S. GDP (Y) captures the effect of the business cycle on prices. Table 1 shows the findings for the estimation period 1986Q4–2015Q2.[17] The first line documents the estimates relating to the price index for the whole industry. The coefficient of real GDP in this case has a value of 0.342 and is statistically highly significant. Hence, prices in this industry are clearly procyclical and this finding makes it clear that petroleum refining is an industry that is likely to benefit from an accurate estimate of long-run frequencies of booms and busts.

The subsequent lines in the table show the results of the price equations for the various subgroups of products. Here we find significant differences for the GDP-coefficients across groups of goods. Diverse values of the γ_2-parameter for different goods indicate that the spread of prices in this industry varies as GDP changes over the cycle. In particular, the price for heavy fuel oil reacts strongest to changes in aggregate output (with a γ_2-coefficient of 0.598) while prices for jet fuels and kerosene barely

[16] A description of this industry and the typical product mix of firms can be found in chapter 5, Office of Technology Assessment (1983). Refineries are in a position to influence the mix of output in a multistage production process and use this flexibility to adjust to changing market conditions (see Gary et al. 2007).

[17] All estimates reported here use logs of level data. Tests for unit roots indicate that all individual prices of refinery products as well as the price of oil and real GDP are non-stationary as indicated by augmented Dickey–Fuller test statistics for the hypothesis of a unit root with a p value of at least 0.3. Hence, in order for the equation in level terms as shown in (8) to have the necessary properties for testing we need to make the case that (8) represents a cointegration equation. This proposition is supported by Dickey–Fuller test statistics concerning the residuals of the estimated equations which indicate stationarity of the residuals in all cases at the 1% level of significance.

Table 1 Regression results for prices in the petroleum industry

Product type	γ_0	γ_1	γ_2	$\bar{R}^2$	SEE	DW
Gasoline	−1.303*	0.863**	0.342**	0.973	0.109	1.551
	(0.638)	(0.025)	(0.075)			
Regular gasoline	−1.181	0.822**	0.314**	0.976	0.116	1.644
	(0.652)	(0.027)	(0.077)			
Premium gasoline	−0.557	0.773**	0.274**	0.966	0.111	1.509
	(0.636)	(0.025)	(0.074)			
Jet fuel	1.001	0.983**	0.036	0.974	0.110	1.688
	(0.719)	(0.035)	(0.113)			
Kerosene, except jet fuel	0.513	1.042**	0.064	0.968	0.135	1.597
	(0.963)	(0.035)	(0.113)			
Home heating oil	−1.148	0.863**	0.313**	0.967	0.120	1.784
	(0.798)	(0.030)	(0.094)			
Diesel fuel	−1.393	0.927**	0.316**	0.973	0.117	1.824
	(0.733)	(0.028)	(0.086)			
Heavy fuel oils	−3.755	0.826**	0.598**	0.967	0.126	1.225
	(0.774)	(0.030)	(0.091)			
Liquefied refinery gases[a]	−3.924	0.323**	0.582**	0.962	0.145	1.443
	(0.774)	(0.030)	(0.091)			

**, * Significance at the 1 and 5% level of significance, respectively. Numbers in parentheses are standard errors of estimated coefficients

[a] Liquefied refinery gases are the only case where the inclusion of a lagged endogenous term is appropriate (its estimated coefficient in this case is 0.530 with a standard error of 0.118)

move with the cycle with γ_2-coefficients of 0.036 and 0.064, respectively. The price responses for gasoline and heating oil to changes in GDP lie between these polar values.

The documented heterogeneity of responses to variations in GDP indicates that the spread of prices in the petroleum refining industry varies markedly over the cycle. This is the requisite for short-term forecasting to be profitable. We can further highlight this effect by focusing on one pair of prices of refinery products which show a markedly different reaction to real GDP. Motivated by the findings from Table 1 we choose the relative price of heavy fuel oil (strong response to GDP) and jet fuel (weak response to GDP). The following shows the result of a regression in which the relative price of these two products is explained:

$$\begin{aligned} ln\left(P_{hf}/P_{jf}\right)_t = & -\underset{(0.837)}{2.547} + \underset{(0.093)}{0.469}\, ln\left(P_{hf}/P_{jf}\right)_{t-1} + \underset{(0.098)}{0.302}\, ln\left(Y_t\right) \\ & - \underset{(0.028)}{0.087}\, ln\left(P_t^{OIL}\right) \qquad (9) \\ \bar{R}^2 = & \quad 0.421, \text{SEE } = 0.106, \text{DW} = 2.157 \end{aligned}$$

Here, the numbers in parentheses below the estimated coefficients show their standard errors. The key coefficient here, with an estimated value of 0.302, gives the elasticity of this relative price with respect to real GDP. As is to be expected this coefficient is both economically significant in the sense of our analysis and statistically significant. In summary, our results show a general movement of selling prices over the cycle combined with a variation of the price spreads. Thus, the oil refining industry tends to benefit from basing capacity choices on an accurate assessment of the relative frequency of expansions and contractions. It further gains from a sharpened short-run forecast that allows it to choose a favorable composition of outputs.

6 Conclusions

The optimization of the output mix over the business cycle is one important way in which producers may benefit from business cycle forecasting. For this operative problem even the small increase in predictive accuracy that active business cycle forecasting has to offer may be well worth its costs. A further, strategic, potential for business cycle assessment relates to the firm's optimal size of operations. Here, an accurate assessment of the relative frequencies of expansion and contraction periods is shown to be the key element business cycle analysis has to offer.

The circumstances in which business cycle forecasting is profitable will not apply to all firms and industries. Some producers will benefit from both an informed short-run forecast and an accurate assessment of business cycle frequencies. The empirical analysis presented in this article indicates that the petroleum refining industry is in this group. Others will only benefit from either a sharpened short-run forecast or an accurate long-run assessment or not at all. Future research will benefit from access to data covering individual firms or groups of firms for which the relevant selling price data across the output portfolio is available. Such data can help identify industries or firms likely to benefit from business cycle forecasts. Let us finally address the question what business can do about business cycle risks besides forecasting. A sizeable literature has studied the possibilities for firms to take precautions for recessions (e.g., Marx 1980; Pearce and Michael 2006). Although precautions for possible downturns such as regional and market-wise diversification may complement business cycle forecasting they will hardly be able to replace it.

References

Achuthan L, Banerji A (2004) Beating the business cycle: how to predict and profit from turning points in the economy. Currency Doubleday, New York

Barro D, Canestrelli E (2014) Downside risk in multiperiod tracking error models. Cent Eur J Oper Res 22(2):263–283

Batchelor R (2009) Forecasting sharp changes. Foresight 17(Spring):7–12

Coibion O, Gorodnichenko Y, Hong GH (2015) The cyclicality of sales, regular and effective prices: business cycle and policy implications. Am Econ Rev 105(3):993–1029

Diebold FX, Rudebusch GD (1990) A nonparametric investigation of duration dependence in the American business cycle. J Polit Econ 98(3):596–616

Diebold FX, Rudebusch GD (1999) Business cycles: durations, dynamics, and forecasting. Princeton University Press, Princeton

Ellis JH (2005) Ahead of the curve: a commonsense guide to forecasting business and market cycles. Harvard Business School Press, Boston
Estrella A, Mishkin FS (1998) Predicting U.S. recessions: financial variables as leading indicators. Rev Econ Stat 80(1):45–61
Ethe S (1956) Forecasting in industry. Division of business practices. National Industrial Conference, New York
Friedman WA (2014) Fortune tellers: the story of America's first economic forecasters. Princeton University Press, Princeton
Gary JH, Handwerk GE, Kaiser MJ (2007) Petroleum refining: technology and economics, 5th edn. CRC Press, Boca Raton
Giliand M (2010) The business forecasting deal: exposing myths, eliminating bad practices, providing practical solutions. Wiley, Hoboken
Gordon RJ (1990) The measurement of durable goods prices. University of Chicago Press, Chicago
Harding D, Pagan A (2010) Can we predict recessions? National Centre for Econometric Research. NCER Working Paper Series: 69
Hudson WJ (1993) Executive economics: forecasting and planning for the real world of business. Wiley, New York
Lewis JP (1959) Business conditions analysis. McGraw-Hill, New York
Liu W, Moench E (2014) What predicts U.S. Recessions? Federal Reserve Bank of New York, Staff Reports: 691
Luedicke H (1954) How to forecast business trends; a special report for executives. Journal of Commerce, New York
Marx TG (1980) The corporate economics staff: challenges and opportunities for the '80s. Bus Horiz 23(2):15–18
Morris RW (1996) Motor vehicles, model year 1996. Bureau of Economic Analysis. Surv Curr Bus 76(11):35–40
OECD (2009) The automobile industry in and beyond the crisis. Econ Outlook 86(2):87–117
Office of Technology Assessment (1983) Industrial energy use. U.S. Congress, OTA-E-198, Washington
Pearce JA II, Michael SC (2006) Strategies to prevent economic recessions from causing business failure. Bus Horiz 49(3):201–209
Rötheli TF (1998) Forecasting among alternative strategies in the management of uncertainty. Manag Decis Econ 19(3):179–187
Rötheli TF (2007) Business forecasting and the development of business cycle theory. Hist Polit Econ 39(3):481–510
Rötheli TF (2008) Estimation of evolutionary models as tool for research in industrial organization. J Socio-Econ 37(1):138–148
Rötheli TF (2012) Boundedly rational banks' contribution to the credit cycle. J Socio-Econ 41(5):730–737
Sephton P (2009) Predicting recessions: a regression (probit) model approach. Foresight Winter(12):26–32
Turner RC (1978) Should you take business forecasting seriously? Bus Horiz 21(2):64–72
Wasson RC (1953) Investment in production equipment. Surv Curr Bus 33(11):11–20
Wheelwright SC, Makridakis SG (1973) Forecasting methods for management. Wiley, New York
Zarnowitz V (1992) Business cycles: theory, history, indicators, and forecasting. University of Chicago Press, Chicago

Data sources

NBER dating of business cycle turning points. http://nber.org/cycles/cyclesmain.html
Industry price data from the U.S. Bureau of Labor Statistics. http://data.bls.gov/cgi-bin/dsrv?pc
Crude oil price (West Texas intermediate). https://research.stlouisfed.org/fred2/series/MCOILWTICO