Naïve Newsvendor Adjustments: Are They Always Detrimental?

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Abstract

Newsvendor problems are an important and much-studied topic in stochastic inventory control. One strand of the literature on newsvendor problems is concerned with the fact that practitioners often make judgemental adjustments to the theoretically “optimal” order quantities. Although judgemental adjustment is sometimes beneficial, two specific kinds of adjustment are normally considered to be particularly naïve: demand chasing and pull-to-centre. We discuss how these adjustments work in practice and what they imply in a variety of settings. We argue that even such naïve adjustments can be useful under certain conditions. This is confirmed by experiments on simulated data. Finally, we propose a heuristic algorithm for “tuning” the adjustment parameters in practice.

Keywords: Inventory; Judgemental adjustments; Demand chasing; Pull-to-centre effect

1 Introduction

Single-period stochastic inventory control problems, known as Newsvendor problems (NVPs), have received much attention from the Operational Research community (see, e.g., the books [9,15,31,36]). In this paper, we focus on the simplest NVP, in which there is only one product. The demand for the product over the selling period is a random variable $d$, with known distribution. The product is purchased before the period at a fixed unit price $v$, and sold during the period at a unit price $p$. If any excess stock remains at the end of the period, a holding cost $c_h$ is incurred per unit. If there is any unsatisfied demand, a shortage cost $c_s$ is incurred per unit.

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For a given $x$ and a given realisation $d$ of $\tilde{d}$, the realised profit $\pi$ over period is:

$$
\pi(x, d) = \begin{cases} 
pd - vx - ch(x - d), & \text{if } x \geq d 
px - vx - cs(d - x), & \text{if } x < d.
\end{cases}
$$

The optimal order quantity that maximises the expected profit is then (2):

$$
x^* = F^{-1}(\tau),
$$

where $F$ is the cumulative distribution function for $\tilde{d}$, $c_o = v + ch$ is the overage cost, $c_u = p - v + cs$ is the underage cost, and the quantile $\tau = c_u / (c_o + c_u)$. We will call a product with $\tau > 0.5$ a “high-margin” product, and a product with $\tau < 0.5$ a “low-margin” product.

In the textbook formulation, it is assumed that one has a correct model of the demand distribution $F$, with correct parameters. In real life, however, correctness is rarely assured and a model typically misses important information. Moreover, even if the model is correct, the parameters may evolve over time (for example, due to market shocks or product innovations by competitors). For these reasons, decision makers often make so-called “judgemental adjustments” to the theoretically “optimal” order quantities. The literature on this topic is extensive (e.g., [4, 5, 6, 7, 22, 23, 30]).

Although judgemental adjustments can exist in many forms (see [27, 14, 18] for example), two specific kinds of adjustment have received most attention in the NVP literature ([4, 5, 7, 22, 23]). The first, called pull-to-centre, means adjusting the order quantity towards the mean demand. The second, called demand chasing, means adjusting it towards the demand in the immediately preceding period. Although these two kinds of adjustment are regarded as especially naïve, considerable evidence for their existence has been found by scholars, and several theories have been developed to explain them ([4, 5, 7, 12, 25, 34]). Yet, to our knowledge, there has not been any numerical study of the effect that these two naïve adjustment mechanisms are likely to have on the long-term expected profit in the NVP.

In this paper, we look at naïve adjustment from a different point of view. We begin by arguing that such adjustments may be useful under certain conditions, due to the fact that any given statistical model of the demand is unlikely to be completely accurate. In particular, we suggest that a modest amount of naïve adjustment may be beneficial in two specific situations that are highly important in practice; namely, (i) when a relatively small amount of demand data is available, and (ii) when the true demand model is unknown. This idea is tested via extensive computational experiments. We then consider the possibility of applying naïve adjustments in an automated fashion. For this purpose, we propose a simple heuristic for tuning the adjustment parameters. Finally, we test the heuristic on a real-life example, with encouraging results.
The paper is organised as follows. In Section 2, we summarise the existing literature. In Section 3, we argue in favour of naïve adjustment, and propose a mathematical model which incorporates both types of adjustment. In Section 4, we conduct experiments on simulated data under different conditions, and discuss the results. In Section 5, we present the tuning heuristic and apply it to a real-life example. Finally, Section 6 contains some concluding remarks.

2 Literature Review

In this section, we review and discuss the existing literature on naïve newsvendor adjustment. Subsections 2.1 and 2.2 are concerned with demand-chasing and pull-to-centre, respectively.

2.1 Demand chasing effect

The demand chasing effect (DC), in the NVP context, describes a phenomenon whereby decision makers tend to adjust their order quantity towards the realised demand in the previous operating period.

To our knowledge, the first paper to give empirical evidence for DC was [30]. They observed decision makers over fifteen consecutive ordering periods, for a selection of products, each with known distribution. They showed that the participants systematically deviated from the optimal order quantity. They also gave a tentative explanation for the phenomenon, based on the avoidance of regret. The idea is that, if decision makers fail to choose the ex-post optimal order quantity in a given period, they regret their decision, which leads them to adjust the quantity in the next period.

After the publication of [30], evidence for DC appeared in many papers. [5] repeated the experiment, but with 100 decision periods. They found that the participants tended to improve over time, but only very slowly. [4] studied the convergence of the participants behaviour, and argued that the order quantities from decision makers converge to a level different from the one which optimises expected profit. Other relevant works include [7, 10, 12, 23, 34].

[22] argued that some of the statistical techniques used in the behavioural experiments were flawed. See the recent paper [20] for a discussion of this issue.

Several models of DC were proposed in the above-mentioned papers. For brevity, we present only the simplest model, which appeared in [7]. It takes the form:

\[ x_t = x_{t-1} + \beta (d_{t-1} - x_{t-1}), \]  

(3)

where \( x_t \) is the actual order quantity in time period \( t \), \( d_{t-1} \) is the realised demand in the previous period, and \( \beta > 0 \) is the DC parameter. A higher \( \beta \)
indicates a stronger demand chasing effect. (In rare cases, one might observe \( \beta < 0 \), as a “pull forward in demand”.)

We remark that the model (3) is equivalent to “simple exponential smoothing” or SES ([8]), in the so-called “error-correction” form. We observe that it ignores the NVP solution and asymptotically converges to the mean demand. Moreover, it assumes a fixed \( \beta \) for all periods, implying that practitioners adjust the orders every period by the same proportion. Fortunately, the latter assumption does not cause serious problems in practice. Indeed, even if practitioners adjust the order with different quantities over time, their behaviour can be modelled on average using (3). Furthermore, there is empirical evidence that, for human decision makers, the value of their \( \beta \) will eventually converge to a single value over time ([30, 35]).

### 2.2 Pull-to-centre effect

The *pull-to-centre* effect (PtC), also known as the mean anchor heuristic, describes a phenomenon when a decision maker adjusts the order quantity towards the mean demand.

To our knowledge, the first paper to give empirical evidence for PtC was again [30]. Their interpretation of PtC is that decision makers order less than the optimal amount for high-margin products, but more for low-margin products. They also discussed several possible causes for the phenomenon, including risk and loss aversion, underestimation of opportunity cost, and waste aversion. They also discussed a possible explanation in terms of “prospect theory” ([19]).

Alternative explanations of PtC include adaptive learning ([4]), decision noise and optimisation error ([32]), overconfidence bias ([28]), and psychological costs associated with leftovers and stockouts ([16]). We remark that [23] argued that some of the statistical techniques used to detect PtC were flawed, just as [22] argued for DC.

There is some evidence that individual differences can affect the behaviour of the decision maker in NVPs. [11] showed that males tend to take more risks than females, which leads them to order more, on average. [10] and [12] showed that differences in nationality correlate with different biases while making newsvendor decisions.

[4] found that decision makers tend to be more biased towards the mean demand in earlier periods than in later periods. This suggests that training could be of some benefit to the decision making. Additional discussions of training effects can be found in [5, 7, 28, 35].

Following the works of [4] and [7], the PtC effect can be expressed mathematically as:

\[ x_t = (1 - \gamma)x_t^* + \gamma \hat{\mu}_t, \quad (4) \]

where \( \hat{\mu}_t \) is the estimated mean demand for the period \( t \) (which can be obtained with a forecasting technique), and \( 0 < \gamma < 1 \) is the PtC parameter.
In this case, the order quantity can be viewed as a weighted average of the “textbook” order quantity $x_i^*$, and the estimated mean $\hat{\mu}_t$. A higher $\gamma$ indicates a stronger PtC effect.

Note that the model (4), like the DC model (3), assumes that the adjustment parameter is constant over time and that adjustments happen on each observation. We argue that these assumptions are reasonable because they express a behaviour on average, similar to how the DC behaviour is modelled via (3).

3 An Alternative Perspective and Model

In this section, we argue that there are some positive aspects to naïve adjustment. We also present a new adjustment model, which allows one to perform demand-chasing and pull-to-centre in combination if desired.

3.1 In favour of naïve adjustment

As one can see from Section 2, the previous literature on judgemental adjustment has assumed, either implicitly or explicitly, that DC and PtC are harmful. In this paper, we take a different point of view: we argue that DC and PtC may sometimes be beneficial in practice. To see why, note that the “textbook” NVP formula (2) applies only when one has an accurate statistical model of the demand distribution. In reality, of course, such a model is rarely available. As a result, the textbook formula may give the wrong answer in practice, either underestimating or overestimating the optimal order level. In some circumstances, therefore, DC and/or PtC might help rather than hinder.

To be more specific, we suggest that a modest amount of “naïve” adjustment may be beneficial in two practically important situations:

1. When the demand model is correct, but there is insufficient data to estimate its parameters accurately.

2. When the demand model is mis-specified.

We will test these hypotheses using simulation experiments in the next section, modelling the two situations.

There is another key difference between our work and the existing literature. As mentioned above, the latter relies almost exclusively on data collected from behavioural experiments with human subjects. Here, by contrast, we will use simulated data, since it allows us to conduct extensive experiments very easily.
3.2 An integrated adjustment model

To proceed, we make some additional remarks about the DC model (3). In our view, it is unlikely to be a good model of human behaviour. Indeed, we have already observed that it effectively estimates the mean demand, and does not take cost information into account.

In an attempt to remedy the above weakness, we now propose a “two-stage” model of naïve adjustment, in which DC takes place after PtC:

\[
\begin{align*}
x'_t &= (1 - \gamma)x^*_t + \gamma \hat{\mu}_t \\
x_t &= x'_t + \beta(d_{t-1} - x_{t-1}).
\end{align*}
\]

(5)

The idea here is that we first take the “textbook” order quantity \(x^*_t\), and apply PtC with parameter \(\gamma\). This yields an adjusted order quantity, here denoted by \(x'_t\). After that, we adjust \(x'_t\) itself, by applying DC with parameter \(\beta\).

Unlike the classical DC model (3), the two-stage model (5) yields non-trivial estimates of the optimal order quantity, rather than merely estimating the mean demand. We remark that we are not claiming that human practitioners actually use such a model consciously. Indeed, it is likely that most decision makers will not make a conscious distinction between the two effects. On the other hand, it seems likely that, in practice, judgemental adjustments may contain elements of both PtC and DC. In any case, our goal is not to explore the behaviour of decision makers in practice, but to investigate whether the model (5) might be useful in the two specific situations mentioned in the previous subsection.

Inserting the first equation in the second one in (5), we obtain a unified formulation for DC and PtC, which summarises the order adjustment in one formula:

\[
x_t = (1 - \gamma)x^*_t + \gamma \hat{\mu}_t + \beta(d_{t-1} - x_{t-1}).
\]

(6)

This makes it clearer that the adjusted order quantity is a linear combination of three terms: system order quantity, mean and actual demand. We will focus our investigation on the case in which the parameters \(\beta\) and \(\gamma\) take values between 0 and 0.5 (This is a common assumption in the literature, e.g. [4, 5, 7]), although the theoretical parameter ranges might be wider.

It is important to note that, for a given \(t\), the estimate \(\hat{\mu}_t\) is itself based on \(d_1, \ldots, d_{t-1}\), and so are the quantities \(x^*_t\) and \(x_{t-1}\). Thus, all three quantities are subject to estimation errors.

4 Experiments on Simulated Data

In this section, we perform extensive computational experiments, to test the two hypotheses as mentioned in the previous section. In Subsection
we describe our methodology. The hypotheses themselves are tested in Subsections 4.2 and 4.3 respectively.

We assume initially that $\tau = 0.7$, a value commonly used in the NVP literature to approximate real-life problems (e.g., fashion retail, nurse staffing) ([1, 21]). We show later in this section that the results of our experiment hold with other NVP parameters as well.

### 4.1 Methodology

The first step is to construct 500 time series, each consisting of 200 consecutive demand realisations, which is sufficiently long as shown in behavioural experiments ([1, 30, 7]). To do this, we use the `arima.sim()` function from the `stats` package in R. We assume that the “true” DGP for the demands is an ARIMA(1,0,1) process, with an initial mean of 10,000. We also assume that the noise term is normally distributed with a standard deviation of 100.

We use an ARIMA model because it is popular in the NVP literature, and we choose a model with two parameters so that we can explore the effects of both over- and under-parametrisation. For a given time series and a given $t = 1, \ldots, 200$, we let $d_t$ denote the demand realisation in the $t$th time period.

Now suppose that we have selected a forecasting model. This can be the correct model, i.e., ARIMA(1,0,1), or an incorrectly specified model, such as AR(1). Suppose also that we have selected the adjustment parameters $\beta$ and $\gamma$. We do the following for each time series:

1. For $t = 21, \ldots, 200$, we use the `arima()` function in the `stats` package to produce maximum-likelihood estimates of the mean and standard deviation of demand in time period $t$. We let $\hat{\mu}_t$ and $\hat{\sigma}_t$ denote these estimates. We note that for $t \leq 20$, the results may be biased due to the shortage of observations.

2. For $t = 21, \ldots, 200$, we use $\tau$, $\hat{\mu}_t$ and $\hat{\sigma}_t$ to compute the “textbook” optimal order quantity for time period $t$ using the formula (2). We let $x^*_t$ denote this quantity.

3. Finally, we simulate the adjustment process with $\beta$ and $\gamma$. To avoid systematic bias, we assume that $x_{20} = d_{20}$. For $t = 21, \ldots, 200$, we assume that the amount ordered at the start of period $t$ follows formula (6).

To quantify the effect of adjustment, we proceed as follows. For a given series and for $t = 21, \ldots, 200$, we compute

$$PPL(x_t) = 100 \left[ \frac{\pi(d_t, d_t) - \pi(x_t, d_t)}{\pi(d_t, d_t)} \right].$$ (7)
We also compute the “relative profit improvement” (also known as “forecast value added” in some contexts (13)):

\[
RPI(x_t) = 1 - \frac{PPL(x_t)}{PPL(x_t^*)}.
\]

(8)

Intuitively, the mean of the \(RPI(x_t)\), over all 500 time series, represents the improvement in profit (if any) gained by using the chosen adjustment in period \(t\). The higher the value is, the better the performance of the approach is. If the value is negative then this means that the approach is worse than the benchmark.

4.2 When the DGP is known

We first report results for the case in which the DGP is known, but the model parameters need to be estimated. In particular, we assume that we are using an ARIMA(1,0,1) model, but with unknown parameters.

In Table 1, we show the mean \(RPI\) for different values of the adjustment parameters. The heading “short dataset” indicates that the mean \(RPI\) is computed over the interval \(t \in [21, 110]\), and the heading “long dataset” indicates that the mean is computed over the interval \(t \in [111, 200]\).

Table 1: Average RPI with varying adjustment parameters and with short/long datasets (\(\tau = 0.7\))

| Short dataset | \(\beta\) | \(\gamma\) | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|---------------|----------|------------|---|-----|-----|-----|-----|-----|
| 0             | -        | 3.5%       | 3.4% | 3.3% | 3.2% | 2.8% |
| 0.1           | 3.5%     | 5.0%       | 4.8% | 4.7% | 4.6% | 3.8% |
| 0.2           | 4.2%     | 5.1%       | 5.0% | 4.6% | 4.0% | 2.4% |
| 0.3           | 2.5%     | 2.8%       | 2.6% | 1.5% | 0.9% | 0.2% |
| 0.4           | -2.4%    | -1.3%      | -1.9% | -3.1% | -3.9% | -5.6% |
| 0.5           | -5.1%    | -3.9%      | -4.4% | -5.9% | -6.8% | -7.7% |

| Long dataset  | \(\beta\) | \(\gamma\) | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|---------------|----------|------------|---|-----|-----|-----|-----|-----|
| 0             | -        | -0.5%      | -0.9% | -1.3% | -1.7% | -2.1% |
| 0.1           | -0.7%    | -0.2%      | -0.5% | -0.7% | -0.9% | -1.3% |
| 0.2           | 0.1%     | 0.3%       | 0.2% | 0.1% | -0.2% | -0.7% |
| 0.3           | -2.1%    | -1.6%      | -2.6% | -3.3% | -4.1% | -5.1% |
| 0.4           | -6.7%    | -6.4%      | -7.5% | -8.4% | -9.2% | -10.2% |
| 0.5           | -11.1%   | -10.5%     | -11.8% | -12.8% | -13.8% | -14.7% |

Table 1 indicates that a modest amount of adjustment can be beneficial, especially when the number of historical demand observations is short. This is possibly due to the statistical model being unable to estimate its parameters accurately on insufficient data. Therefore, modest amount of adjustment can provide additional information. On the other hand, too
much adjustment leads to a loss. We also find that the RPI is more sensitive to the choices of $\beta$, meaning that demand chasing has a bigger influence in this case. We mark that this is also true for other data inputs.

To explore this effect in more detail, we show in Figure 1 a plot of average RPI against the length of the dataset, for three different values of $(\beta, \gamma)$, namely, $(0, 0.4)$, $(0.1, 0)$ and $(0.2, 0.1)$. It can be seen that the average RPI is well above zero initially, but decreases, and eventually becomes negative.

Figure 1: Average RPI of judgemental adjustments vs. dataset length ($\tau = 0.7$)

A tentative explanation is that the maximum-likelihood estimates of $\hat{\mu}_t$ and $\hat{\sigma}_t$ are prone to errors when the number of observations is small. It may even be that the estimates suffer from some kind of systematic bias, which decreases over time. By performing a small amount of adjustment, we shift the order quantity toward the true optimal value. We would expect this effect to vanish as more data becomes available.

In Figure 2, we use a heat map to compare the performance of adjustment with different parameter values, for the case in which the number of past observations is exactly 20 (i.e., $t = 21$). As we observed in Figure 1, the dominance relationship between parameter pairs (one parameter pair generating higher RPI than the other) is not influenced by data length. Therefore, the choice of $t = 21$ can amplify the results, making it easier for us to observe. One can clearly see from Figure 2 that large adjustments are harmful, while modest amounts of adjustment, on the other hand, can generate positive RPI. From our data, the most profitable option is to set $\beta$ to around 0.2 and $\gamma$ to around 0.05. A possible explanation to this phenomenon is that the “textbook” order quantity will be close to the theoretical one, but it would need to be adjusted by the order quantity and demand on the
previous observation. The PtC effect needs to be reduced in comparison with the DC effect.

Next, we examine the effect of $\tau$ on the performance of adjustment. Figure 3 shows boxplots of the RPI for four different values of $\tau$ (0.3, 0.5, 0.7 and 0.9), and the same three values for $(\beta, \gamma)$ as before. Here, $t = 21$ as before. Each boxplot shows the range, median and quartiles over the 500 time series.

Interestingly, adjustment yields a benefit in every case, except when $\tau = 0.5$. Moreover, we can see in Figure 3 that the performance of adjustments when $\tau = 0.3$ is very similar to that when $\tau = 0.7$. This suggests that the effect of adjustment may be symmetric around 0.5. Note also that, even when $\tau = 0.5$, adjustment does not cause any noticeable loss of profit.

All things considered, it appears that, when the model is correct but the data length is short, a modest amount of naïve adjustment can be beneficial instead of harmful. This goes against the prevailing view in the literature that DC and PtC are invariably damaging. We believe that the discrepancy is mainly due to the model correctness assumption made in the literature. When model correctness is assured, there is no doubt that any kind of adjustment will be harmful to the profit. Indeed, the behavioural results are in line with the results that we obtained with the longest datasets in our experiment, where there was sufficient data to properly estimate all parameters.
4.3 When the model is misspecified

In this subsection, we examine the effect of model misspecification on the relative performance of the judgemental adjustments. We consider three scenarios of model misspecification:

1. The model is under-parametrised (i.e., omits one or more important variables), which typically leads to biased estimates of parameters;

2. The model is over-parametrised (i.e., has one or more redundant variables), which usually leads to inefficient estimates of parameters;

3. The model has the correct parameters, but the assumed distribution of the error term is wrong, which can lead to biased quantile estimates.

For scenario #1, we use an MA(1) model to fit the underlying demand data. For scenario #2, we use an ARIMA(2,0,1) model. For scenario #3, the data is generated using a modified version of ARIMA model, in which the error term follows the Laplace distribution instead of the normal distribution. When estimating the optimal order quantity, however, we use the incorrect assumption that the error term follows the normal distribution.

Since we wish to focus on the effect of model misspecification, rather than the effect of a lack of data (as in the previous subsection), we report the mean RPIs when $t = 200$, when plenty of demand data is available. As before, however, all means are taken over 500 time series.

Figure 4 shows the boxplots for scenarios #1 and scenario #2, together with the boxplots for the correctly specified case, for comparison.
is equal to 0.7. As before, results are reported for three different settings of \((\beta, \gamma)\).

Figure 4: Boxplots of the RPI for three different models and three different combinations of adjustment parameters \((\tau = 0.7, t = 200)\)

\[
\begin{array}{|c|c|c|}
\hline
\text{Parameter} & \beta=0.1, \gamma=0 & \beta=0.2, \gamma=0.1 & \beta=0, \gamma=0.4 \\
\hline
\end{array}
\]

It is apparent that, when the forecasting model omits important variables, naively adjustment can yield significant increase in profit. The improvement seems to be present also when the model has redundant variables, but the effect is less pronounced. This is probably due to the nature of judgemental adjustment. In the case where important information is omitted from the model, there is a good chance that adjustment can provide supplementary information. On the other hand, when the model contains redundant variables, no additional information is needed.

Heatmaps for scenario #1 and scenario #2 are presented in Appendix A. They confirm again our findings in Figure 4. It appears that the optimal PtC parameter \((\gamma)\) is larger than the optimal DC parameter \((\beta)\) in the underparametrised case. This is probably because omitting variables in the model leads to an over-estimate of the variance, leading to order quantities that are further from the mean than required. This bias is remedied by using PtC, since the order quantity is brought closer to the mean of the data. On the other hand, the improvement from adjustment when the model has redundant variables is limited, because the model overfits the data, thus having a variance biased towards zero.

Finally, we consider scenario #3, in which the underlying assumption on the error term distribution is wrong. Figure 5 shows the RPI boxplots for this case. It can be seen that adjustment significantly improves the expected profit when \(\tau = 0.9\), but the effect disappears when \(\tau = 0.5\). This can be explained by the relative shapes of the normal and Laplace distributions.
Since the largest difference between the distributions is in the “tails”, more adjustment will be needed when $\tau$ is at an extreme value (i.e., close to either 0 or 1).

Figure 5: Boxplots of the RPI when assumed distribution of error term is wrong ($t = 200$)

Interestingly, PtC seems to be of more benefit than DC in scenario #3. This is probably because the wrong assumption about the error term distribution leads to a systematic over-estimation of the variance. Just as in the under-parametrised case, this over-estimation alleviated by PtC.

Once again, we find that naïve adjustments can be beneficial instead of harmful. The results are similar to what was found in Subsection 4.2 and can be overall summarised as:

1. DC is more useful in the short data length case. This is probably because of the small sample bias, which vanishes on larger samples.

2. PtC is more beneficial than DC in the case of model misspecification. This is because of the systematic underestimation of variance in case of omitted variables or wrong model form.

3. In the case when the DGP is known, the benefits from adjustments only depend on data length and adjustment parameters.

4. The improvement from adjustments appears when the model omits important variables, or the distributional assumption is wrong.

5. When the model has redundant variables, the improvement from both DC and PtC is less pronounced.
In general, we can conclude that DC is likely to be beneficial when there is a shortage of demand data, whereas PtC is likely to bring value when the model is misspecified. The combination of the two should be beneficial in practice where the model is not known and the samples of data are limited.

5 Tuning Algorithm

In the previous section, we showed that naïve adjustments can improve the expected profit when the data is insufficient and/or the demand model is misspecified. It is however not clear how one might choose suitable parameter values when faced with a specific NVP instance. In this section, we propose and test a simple heuristic algorithm for parameter “tuning”. We believe that this tuning algorithm may be of interest to both academics and practitioners. The method is explained in Subsection 5.1. In Subsection 5.2 we apply our method to a real-life NVP instance, for which the true model is not known. Finally, in Subsection 5.3 we present and compare the results with and without the application of adjustment with “tuned” parameters.

5.1 Procedure

Let us suppose that we have a forecasting model that, for each period in the training set, \( t \in [1, s] \), is able to provide an estimate of the mean demand \( \hat{\mu}_t \). Moreover, let us assume that we are also able to estimate the “textbook” optimal order quantity \( x^*_t \). We remind the reader that our adjusted order quantity takes the form:

\[
x_t = (1 - \gamma) x^*_t + \gamma \hat{\mu}_t + \beta (d_{t-1} - x_{t-1}).
\]

The \( x_t \) can be calculated for all \( t \in [1, s] \) based on the available mean and actual demand, the “textbook” order quantity and some values of \( \beta \) and \( \gamma \). To determine the values of parameters, we solve an optimisation problem over the training set. Following suggestions in [3] and [24], we use a non-standard “loss function” for this purpose. The function is chosen to maximise the profit over the training set, instead of minimising the MSE or MAE in the usual way. That is, we estimate \( \beta \) and \( \gamma \) by maximising the in-sample empirical profit:

\[
\max_{\beta, \gamma} \sum_{t=2}^{s} \pi(x^*_t, \hat{\mu}_t, x_t, d_t). \tag{9}
\]

We remark that the function to be maximised in (9) is continuous and concave. On the other hand, it is not differentiable in general. This means that in order to maximise the profit we need to use derivative-free optimisation algorithms, such as Nelder-Mead ([26] [29]).
5.2 Real life example

Here we present an example of application of our approach to real data. The data we use comes from a medium-sized grocery store which sells a wide range of products, many of which are perishable. It includes daily demands for each product, for a period of around 9 weeks, which ran from mid-October to December. For this study, we selected four typical products with very different data structures and NVP parameters. In particular, we made sure that the selected products have a range of prices, demands and critical quantiles, in order to make the experiment less biased. For reasons of confidentiality, we refer to these products as simply A, B, C and D.

To give reader some sense of the data, we provide time-series plots in Figure 6 and summarise the cost parameters in Table 2.

![Figure 6: Demand time-series for real-life case](image)

### Table 2: Data for a subset of the products

| Products | Price and Costs | Critical Quantile |
|----------|----------------|-------------------|
|          | $p$ $v$ $c_h$ $c_s$ |                  |
| $A$      | 2.96 1.28 0.49 0.51 | 0.55              |
| $B$      | 11.98 4.13 2.49 1.33 | 0.58              |
| $C$      | 2.86 1.96 0.78 0.56  | 0.35              |
| $D$      | 4.29 3.24 1.03 0.21  | 0.23              |

Following standard practice in forecasting, we use a rolling-origin method ([33]), with constant in-sample size. For each product, on each iteration, we
use three-fifths of the data as the training set, and perform a one-step-ahead forecast.

To perform a fair comparison, and reduce the possibility of bias in our choice of model, we simply applied one of the most popular automatic techniques for forecasting: the `ets()` function from the R `forecast` package (\[17\]). This function attempts to select the most appropriate ETS model, using the Akaike Information Criterion. The pre-tuning decision \(x_t^*\) is computed using the output from the traditional forecasting procedure, while the tuned decision \(x_t\) is computed using the output from the forecasting and tuning procedures in combination.

### 5.3 Results

We now present the results obtained with our tuning algorithm. Figure 7 displays box-plots of the RPI, taken over the iterations, for each of the four products. We remind the reader that a positive RPI indicates that adjustment has been beneficial (see Subsection 4.1). The plots indicate that the RPI is positive for all four products in all the situations. Thus, the tuned order decisions outperform the pre-tuned ones for all four products.

![Boxplot of the out-of-sample RPI. The black lines in the boxes represent mean values.](image)

Table 3 summarises performance in terms of service levels. The row labelled ‘target’ shows the critical quantile that maximises the expected profit for the given cost and price parameters. The next two rows show the achieved service level without and with tuning, respectively. In all four cases, the achieved service level with tuning is much closer to the target one than the one without tuning.

To gain additional insight, we repeated the entire experiment using four
Table 3: Achieved Service level of each methods

|          | Product A | Product B | Product C | Product D |
|----------|-----------|-----------|-----------|-----------|
| Target   | 0.55      | 0.58      | 0.35      | 0.23      |
| Pre-tuning | 0.75  | 0.80      | 0.13      | 0.17      |
| Tuned    | 0.65      | 0.62      | 0.25      | 0.29      |

other popular forecasting methods. The results are presented in Table 4. From the table, one can see that the tuning algorithm yields a positive out-of-sample RPI in every single case.

Table 4: RPI results obtained when using adjustment with other forecasting methods

| Products  | Methods | In-sample | Out-of-sample |
|-----------|---------|-----------|---------------|
| Product A | Mean    | 4.2%      | 2.8%          |
|           | S-Mean  | 0.4%      | 2.4%          |
|           | S-Naïve | 3.0%      | 2.4%          |
|           | ARIMA   | 1.0%      | 0.4%          |
| Product B | Mean    | 3.9%      | 4.1%          |
|           | S-Mean  | 1.1%      | 2.9%          |
|           | S-Naïve | 2.5%      | 2.8%          |
|           | ARIMA   | 1.9%      | 1.2%          |
| Product C | Mean    | 4.1%      | 4.2%          |
|           | S-Mean  | 2.8%      | 2.2%          |
|           | S-Naïve | 2.6%      | 2.5%          |
|           | ARIMA   | 0.2%      | 1.1%          |
| Product D | Mean    | 4.8%      | 3.1%          |
|           | S-Mean  | 1.2%      | 3.5%          |
|           | S-Naïve | 3.3%      | 4.5%          |
|           | ARIMA   | 2.6%      | 1.1%          |

The experiment in this section supports our findings in the simulation study. We show that because the true model is not known, the proposed tuning algorithm leads to improvements, bringing the order closer to the correct level.

6 Concluding Remarks

Although there is a considerable literature on judgemental adjustment for newsvendor problems, it has been assumed up to now that ‘demand chasing’ and ‘pull-to-centre’ are especially naïve, and likely to lead to losses in profit. In this paper we have shown that, surprisingly, these adjustment procedures can lead to increased profits in some situations. In particular, they can be useful when (a) there is not enough data available to estimate parameters accurately, and (b) the demand model is misspecified. Interestingly, DC
appears to be more useful under condition (a), while PtC seems to be of more benefit under condition (b). In general, this is because in case of (a) the order estimates suffer from some kind of systematic bias due to short data length; while in the situation (b) the estimated variance is often higher than needed.

We also proposed a simple heuristic for tuning the adjustment parameters. Using a real-life example, we show that the tuned orders outperform the pre-tuned ones in terms of the achieved profit, and also led to a service level closer to the target one.

There are several interesting topics for further research. First, one could attempt to characterise other scenarios under which naïve adjustments tend to be beneficial. Second, one could examine the effects of other forms of adjustment. Third, it might be beneficial to conduct behavioural experiments, in the lab and/or field, to confirm the simulation results. Finally, it would be interesting to extend the research to multi-item newsvendor problems, either with or without substitution effects between products.

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A Heatmaps for model misspecification

Figure 8: RPI heat map for the under-parametrised case ($\tau = 0.7, t = 200$)

![Under-parametrised RPI heatmap](image1)

Figure 9: RPI heatmap for the over-parametrised case ($\tau = 0.7, t = 200$)

![Over-parametrised RPI heatmap](image2)