4. Extended Decision Model Incorporating Cost-Stickiness

In 1994 Noreen and Soderstrom formulated two important statements:[119] First, the relation between overhead costs and activities is **not** strictly proportional and second, whereas the design of more sophisticated cost systems incorporating the non-proportional cost behavior may be costly, in an environment where costs are decision relevant, the implementation of such accounting methods is recommended.

This phenomenon has already been targeted in Germany in the early thirties of the last century, e.g. Strube (1936) investigated and documented cost behavior patterns. The asymmetry of overhead costs to changes in activity has been documented since then in many publications.[120] Naming the phenomenon *"sticky"*, Anderson, Banker and Janakiraman (2003) refer with this term to differences in the extent of increases and decreases in costs corresponding to equivalent in-/decreases in activity. A good example is the German economy, where labor costs can more easily be increased than decreased in times of economic downturn, because of union power and strict labor laws.[121]

Up to this point managerial research has focused on discovering and explaining the sticky costs phenomenon. Homburg (2004) develops a method for binary portfolio decisions, incorporating asymmetric cost-behavior. Building on this methodology, this chapter widens the focus on pricing decisions incorporating sticky cost-behavior. The assumption is, that costing systems neglecting cost stickiness are, for one, unable to reflect real cost consumption and therefore, for the other, lead to biased decisions.

[119] See Noreen and Soderstrom (1994), pp. 273-274.

[120] E.g. Noreen and Soderstrom (1997); Anderson, Banker and Janakiraman (2003); Banker, Byzalov and Plehn-Dujowich (2014).

[121] See Banker and Chen (2006), p. 26, or Calleja, Steliaros and Thomas (2006), p. 133.

P. Plank, *Price and Product-Mix Decisions Under Different Cost Systems*,
Quantitatives Controlling, DOI 10.1007/978-3-658-19321-8_4

To find evidence for this assumption the research framework of the previous chapter is changed in the following: Cost-stickiness is included in the benchmark model. But instead of having only one type of noisy models, this approach uses two different noisy models: one neglecting and one incorporating cost-stickiness.[122] The details of the sticky implementation will be covered in depth later. For now let's assume the BM considers cost stickiness and the performance of non-sticky noisy models, i.e. the heuristics are kept unchanged, is measured analogously to the approach of chapter 3. In accordance with the above formulated assumption the performance of the noisy model should drop.

The line of argument is as follows: Demand changes lead to short-term capacity changes over time, in addition to the installed and per period available long-term capacity. It can be assumed, that due to cost-stickiness, these capacity adjustments are costly and short-term installed capacity can only be disinvested, if needed, at a premium. Based on the mechanics of the (unchanged) NM, the NM is unable to adjust its cost allocation process to changes in demand over time. Additionally it is unable to cope with different costs for capacity buildup and divestment. The NM allocates costs via heuristics directly to products. The heuristics yield activity costs which are stable over time and are therefore unable to reflect changes in demand nor to align costs in respect to the direction of resource adjustment. Therefore, leaving the heuristics unchanged, the NM should yield lower profits.

Whereas it is a first goal of this chapter to show, that the performance of the NM drops, the main idea is to install NMs that are able to cope with the cost-stickiness effect. The key for this lies with the short-term capacity adjustments, as they are mainly driven by cost-stickiness. The size of short-term adjustments itself is driven by fluctuations in market size (A_{it}). Hence the NM adjustment should focus on these changes. It will be later discussed

[122] Since the research framework is identical in terms of how the research is conducted methodologically, a detailed description of the DOE phases as in Lorscheid, Heine and Meyer (2012) is neglected in the following.

how this adjustment takes place, but the - enhanced - new NM should therefore be able to yield lower profit errors.

While the previous paragraphs abstractly touched on the approach, in the following the basic metrics will be introduced to answer the research questions of this chapter:

(1) How big is the lever of the new NM? This is covered by comparing the new BM profits with the enhanced NM profits.
(2) How severe is the loss in cost-system performance by neglecting cost-stickiness? This is achieved by comparing the result of research question (1) with the delta in profits of the new BM against the old NM, i.e. the usage of the old heuristic set.
(3) And lastly it can be shown how a NM hast to be designed to control for cost-stickiness.

The answer to these questions are very important to researchers and practitioners, as this enables them for the first time to measure the loss caused by cost-stickiness and gives them a starting point of how to adjust their cost-systems in the future.

The remainder of this chapter gives a broader introduction on cost-stickiness, followed by how the research framework is transformed to model sticky cost behavior introducing an enhanced cost allocation process.

4.1 A Side Note on Cost-Stickiness and its model implications

The fundamentals behind cost-stickiness have been shortly addressed in the previous chapter. This chapter aims at backing the intuition of integrating cost stickiness into the decision model and documents its contribution to the literature body. Additionally it is also identified which source of cost-stickiness will be implemented. It is neither a comprehensive overview of cost-stickiness nor a discussion of its empirical evidence, since this would only add limited value for the development of the enhanced simulation model.

Since Anderson, Banker and Janakiraman (2003) developed one of the central concepts to measure cost-stickiness, empirical evidence has been found also in cross country studies (e.g. Banker and Chen (2006)) or as an effect of incentive systems (Dierynck, Landsman and Renders (2012)).[123] A new discussion led by Balakrishnan, Labro and Soderstrom (2014) and Banker and Byzalov (2014) on the used methodology and the role of cost structure towards sticky costs will be taken up in the discussion of the results.

Independent of all the research efforts on finding evidence and explaining cost-stickiness, neither in practice nor in theory, traditional costing has been explicitly modified to control for sticky behavior in the relation between activity levels in the current, past or future period.[124]

Where traditional costing only distinguishes between fixed and variable costs related to changes in activity volume, the sticky model adds costs resulting from resource commitment decisions.[125] Because of their partly lumpy character the latter category cannot be changed as an immediate response to demand changes. Considering the question “why are costs lumpy”, prior research has come up with multiple considerations.

Following Mahlendorf (2009) two basic differentiations group the source of sticky costs due to adjustment delays (unavoidable) and managers’ deliberate decisions (avoidable). The adjustment delay theory is straight forward: costs cannot be adjusted (mostly declined) in the same period as volume changes occur.[126] This leads inevitably to idle capacity costs. On the other hand, the deliberate decisions theory clusters entrepreneurial intended and unintended cost sources. Unintended costs result from agency issues.

[123] For a detailed discussion of the cost-stickiness literature body I refer to Baumgarten (2012).
[124] See Banker, Byzalov and Plehn-Dujowich (2014), p. 840.
[125] See Anderson, Banker and Janakiraman (2003), p. 48.
[126] See Baumgarten, Bonenkamp and Homburg (2010), p. 3.

Instead of optimizing shareholder value, management maximizes its personal value. The buzz word in this context is empire building, meaning self-centered management uses sales growth periods to build up capacity in their domain (i.e. employer stock in their own department), whereas they refrain from giving up these resources in periods of sale declines.[127] The source of this behavior can be manifold: one possible argument is misleading incentive systems.[128]

Incentive schemes are not the only factor driving the decision process. Another factor is expectations of future developments and the inherent consideration if an adjustment of capacity economically makes sense, i.e. the costs of adjustment are below the costs resulting from idle capacity. Whether adjustments have to be made in the first place, depends therefore on the prediction of future sales. It is more likely that management is willing to adjust capacity upwards in times of sales growth than in periods of economic distress. In the latter environment, management decision is not consequently a reduction of capacity, if the persistence of sales declines is expected to be short. Whereas managers aim to reduce adjustment costs, they trade off capacity utilization and respectively their cost over a longer period of time, against adjustment costs in the actual period.[129]

Both, benchmark and noisy model do not incorporate agency theory elements. Therefore only the adjustment delay theory is reflected in the new approach. The following chapter covers the extension.

4.2 The Extended Model Approach

The aim of this chapter is to develop the extended model and clarify the design decisions. Recapitulating the introduced research questions, the

[127] See Chen, Lu and Sougiannis (2012); Kama and Weiss (2013), p. 203.

[128] See Dierynck, Landsman and Renders (2012), p. 1220; Banker, Byzalov and Plehn-Dujowich (2014), p. 847.

[129] See Banker, Byzalov and Plehn-Dujowich (2014), p. 860.

approach has to measure both, the effect of neglecting cost stickiness and the gain by incorporating it into decision making.

The task of the BM model still is to reflect optimal decisions in an environment of perfect information. As it is the reference point, performance of the NM will be measured against it, it is obvious that this model has to incorporate cost stickiness. To separate it from the former BM, the cost-stickiness enhanced BM will be identified by the index "ext" (BM^{ext}). In addition we need two NM: one is the unchanged NM of the last chapter, from here on classified as the standard NM (NM^{std}). The second one is the new NM (NM^{ext}), extended to control for cost-stickiness. Therefore the simulation process also has to be adjusted, first calculating the BM^{ext}, followed by the NM^{std} and subsequently the NM^{ext}. This alignment of the simulation will be the subject of chapter 4.2.3.

4.2.1 The BM adjustment

Following the cost-stickiness introduction, adjustments in capacity follow demand fluctuations. Moreover, reducing installed capacity is more costly than installing additional capacity. Lastly, built up resource costs of previous periods need to have an impact on the resource costs in the current period. This is basically what separates the standard BM (chapter 3) from the extended BM^{ext}.[130]

$$\max_{P_{it}^{BM}, R_{jt}, L_j} \sum_{t=1}^{T} \left(\sum_{i=1}^{I} (P_{it}^{BM} - v_i)(A_{it} - b_i P_{it}^{BM}) - \sum_{j=1}^{J} \phi_j c_j R_{jt} \right) - T \sum_{j=1}^{J} c_j L_j \tag{28}$$

Equation (28) displays the standard benchmark model. One could argue that the term $\sum_{j=1}^{J} \phi_j c_j R_{jt}$ already covers sticki-costs. Adjustments in

[130] See Banker, Byzalov and Plehn-Dujowich (2011), pp. 2–3.

capacity (R_{jt}) are time dependent and one unit of additional capacity costs the standard costs c_j plus a premium rate in costs ($\phi_j > 1$).

This only partially reflects the sticky-cost function. First, it does not differentiate between premiums for investing and divesting capacity. Second, capacity is only installed for one period.

Hence the adjustment is threefold:

(1) The premium ϕ_j is split into a premium for costs of building up capacity (ϕ_j^+) and one for reducing capacity (ϕ_j^-). Obviously the premium for divestments needs to be greater than the premium for investments ($\phi_j^- > \phi_j^+$). Consequently the costs for a short term capacity divestment of resource j ($c_j^- = \phi_j^- c_j$) is higher than the costs for investments ($c_j^+ = \phi_j^+ c_j$).

(2) The buildup of short-term capacities R_{jt} is now persistent, meaning that adjustments are still periodically possible, but built capacities from one period are now kept until they are used or divested. Therefore R_{jt} is the sum of resources of previous periods (R_{jt-1}), the current invest (R_{jt}^+) and the divest (R_{jt}^-). Hence, it is better to refer to these resources as mid-term capacity, instead of short-term capacity.

(3) Due to the split in the cost premium and the resulting differences in costs for mid-term investments and respectively divestments, the profit function (see eq. (29)) needs to be adjusted. The sum $\sum_{j=1}^{J}\left(c_j R_{jt} + c_j^+ R_{jt}^+ + c_j^- R_{jt}^-\right)$ reflects these changes, incorporating costs for the already built up resources ($c_j R_{jt}$), as well as for investments and divestments ($c_j^+ R_{jt}^+ + c_j^- R_{jt}^-$).

The optimal solution renders $Profit^{BM^{ext}}$:

$$\max_{P_{it}^{BM^{ext}}, R_{jt}, R_{jt}^{+}, R_{jt}^{-}, L_j}$$

$$\sum_{t=0}^{T} \left(\begin{array}{c} \sum_{i=1}^{I} \left(P_{it}^{BM^{ext}} - v_i\right)\left(A_{it} - b_i P_{it}^{BM^{ext}}\right) - \\ \sum_{j=1}^{J} \left(c_j R_{jt} + c_j^{+} R_{jt}^{+} + c_j^{-} R_{jt}^{-}\right) \end{array} \right) - T \sum_{j=1}^{J} c_j L_j \quad (29)$$

$$\begin{aligned} \textit{subject to} \quad & \sum_{i=1}^{I} m_{ij} \left(A_{it} - b_i P_{it}^{BM^{ext}}\right) - R_{jt} - L_j \leq 0 && \forall j, t, \\ & \left(A_{it} - b_i P_{it}^{BM^{ext}}\right) \geq 0 && \forall i, t, \\ & R_{jt} = R_{jt-1} + R_{jt}^{+} - R_{jt}^{-} && \forall j, t, \\ & c_j^{+} = \phi_j^{+} c_j && \forall j, \\ & c_j^{-} = \phi_j^{-} c_j && \forall j, \\ & P_{it}^{BM^{ext}}, R_{jt}, R_{jt}^{+}, R_{jt}^{-}, L_j \geq 0 && \forall i, j, t. \end{aligned}$$

Decision variables:		Non-decision variables:	
$P_{it}^{BM^{ext}}$	Optimal price for product i in period t of the BM	A_{it}	Market size per product i and period t
L_j	Initial long-term capacity for resource j (available every period)	b_i	Price elasticity of product i
R_{jt}	Flexible mid-term capacity for resource j and period t	v_i	Variable cost of product i
R_{jt}^{+}	Invest in mid-term capacity for resource j and period t	c_j	Base resource costs of resource j
R_{jt}^{-}	Disinvestment in mid-term capacity for resource j and period t	c_j^{+}	Resource costs for additional resources
		c_j^{-}	Resource costs for divested resources
		ϕ_j^{+}	Premium price for investing in additional capacity of j
		ϕ_j^{-}	Premium price for disinvesting capacity of j
		m_{ij}	Resource consumption matrix for product i and resource j

Based upon Balakrishnan and Sivaramakrishnan (2002), p. 12.

Aside from these changes the extended benchmark model follows the mechanics of the BM of chapter 3. Over a planning horizon of $t=1,\dots T$ periods the BM^{ext} optimizes prices and capacities simultaneously for products $i=1,\dots,I$ and resources $j=1,\dots,J$.

4.2.2 The NM adjustment

As discussed in the introduction of this chapter, we need two noisy models, the standard NM^{std} and the extended NM^{ext}. The extension itself has only been shortly addressed and is the subject of this chapter.

As already stated, the allocation process of costs needs to be refined. If one follows this line of thought, two elements need to be incorporated into the NM: The change in demand over time and the direction of resource changes, i.e. buildup or reduction of capacity.

An obvious starting point would be the heuristics, which steer the allocation process. This is maybe an intuitive starting point for the adjustment. But for two reasons it is hardly possible to control for cost-stickiness at this level.

$$\max_{P_{it}^{NM^{std}}} \sum_{t=1}^{T}\sum_{i=1}^{I}(P_{it}^{NM^{std}} - v_i - ABC_i\ )(A_{it} - b_i P_{it}^{NM^{std}}) \tag{30}$$

The heuristic output is essentially the activity cost vector ABC_i. According to the profit function of the standard NM^{std} (30), these costs are independent of the produced quantity $q_{it} = (A_{it} - b_i P_{it}^{NM^{std}})$. Setting the activity costs for product i, the NM^{std} subsequently optimizes the prices $P_{it}^{NM^{std}}$ and consequently also the production quantity. Hence at the time the NM^{std} sets activity costs, the production quantity has not been determined. In addition, as covered in section 3.1.4, the capacity decision has not taken place. A distinction between costs of resource increase and decrease is therefore impossible.

Focusing on the capacity decision another aspect comes into play: Resources are used across products, therefore only the complete portfolio decision determines the needed resource quantities. Ceteris paribus, a sticky cost-factor taking into consideration changes in resource consumption triggered by changes in market size, can only be applied on a portfolio level.

Further, it needs to be considered, that the higher the fluctuations in market size, the higher the fluctuations in demand are and the lesser the standard NM^{std} is able to cope with the effect.

Homburg (2004) calls demand fluctuation, demand heterogeneity and develops a portfolio based driver, which controls for costs induced by these fluctuations. In the following a driver is developed to enhance the standard NM^{std}, enabling the resulting extended NM^{ext} to cope with cost stickiness.

Homburg (2004)'s profit function is based on the alternation of different portfolio constellations, which are binary decisions: include a certain product in the mix or not. In this publication the price determines the product mix, therefore the approach is different to the underlying publication by Homburg (2004).

The basic idea is to estimate the cost gap resulting from neglecting cost-stickiness in the NM^{std} in comparison to the BM^{ext}. By closing this costing gap, the extended model NM^{ext} should also be able to reduce the profit error towards the BM^{ext}. The question is, whether there exists a functional relation between the costs induced by demand heterogeneity and the resulting cost gap, emerging from capacity differences between the NM^{std} and the BM^{ext}?

The demand heterogeneity can be expressed as the change in demand between the actual and the previous period valued by the costs for these resources. More explicitly for the complete time frame the delta in quantity can be expressed as $\sum_{t=2}^{T}\left|\sum_{i=1}^{I} m_{ij}\left[(q_{it})-(q_{it-1})\right]\right|$. The resource consumption matrix is used to trace back the quantity to resources. To economically quantify the heterogeneity, this delta needs to be valued by a cost factor incorporating the different cost-components for investments and divestments $\left(\phi_j^+ c_j + \phi_j^- c_j - c_j\right)$. In sum the resulting heterogeneity driver $h_{cs}(P_{it})$ can be expressed as:[131]

$$
\begin{aligned}
h_{cs}(P_{it}) = \sum_{j=1}^{J} \big(\phi_j^+ c_j + \phi_j^- c_j \\
- c_j\big) \sum_{t=2}^{T} \left| \sum_{i=1}^{I} m_{ij} \left[\left(A_{it} - b_i P_{it}\right)\right.\right. \\
\left.\left. - \left(A_{it-1} - b_i P_{it-1}\right)\right]\right|
\end{aligned} \tag{31}
$$

Based upon Homburg (2004), p. 338

In other terms, the heterogeneity driver expresses the error the standard NM^{std} makes by neglecting the costs of demand changes. By using the yielded prices P_{it}^{std} by the NM^{std}, one is able to calculate the error for each noisy model, i.e. calculating $h_{cs}(P_{it}^{std})$.

Hereby one component of the functional relation between NM^{std} and BM^{ext} has been identified. The other component is the capacity difference emerging from the inability of the NM^{std} to cope with the demand heterogeneity. To measure the capacity difference by the NM^{ext} the pseudo capacity estimation of section 3.1.4 is used. In other terms, it is the economic valuation of the produced quantity x_{it} by the activity costs ABC_i. The costs of capacity of the BM^{ext} is obviously the sum of medium term and long term capacity valued by the corresponding cost vectors. The delta in costs between both models can therefore be expressed as:

$$
\begin{aligned}
\Delta C(P_{it}^{NM^{std}}) = & \sum_{t=1}^{T} \sum_{j=1}^{J} \left(c_j L_j + R_{jt} c_j + c_j^+ R_{jt}^+ + c_j^- R_{jt}^-\right) \\
& - \sum_{t=1}^{T} \sum_{i=1}^{I} ABC_i \ \left[\left(A_{it} - b_i P_{it}^{NM^{std}}\right)\right]
\end{aligned} \tag{32}
$$

Based upon Homburg (2004), p. 338

[131] The subscript ‘cs’ identifies variables as cost-stickiness enhanced.

To recapitulate, the idea is to develop an extended NM^{ext} that is able by closing the costing gap (in comparison to the BM^{ext}) caused by cost-stickiness to yield better pricing decisions and hence higher profits. It was considered that therefore a cost driver on portfolio level needs to be developed. Generally speaking, the cost driver rate should reflect the structural error the NM^{std} generates. This error can be expressed as the resulting false capacity decision based on neglecting the demand heterogeneity. In addition one can state, that the higher the demand heterogeneity the higher the capacity error. In line with Homburg (2004), assuming the functional relation between h_{cs} and ΔC is linear, the slope of this function can be considered the cost driver rate. Therefore in accordance with eq. (33) the slope π_{cs} describes how intense a change in heterogeneity (h_{cs}) effects the cost gap or in other words the cost error (ΔC) of the NM^{std}.

Following Homburg (2004) the functional relation between the demand heterogeneity and the delta in costs can therefore be expressed as follows:

$$\Delta C(P_{it}^{NM^{std}}) = \beta_0 + \pi_{cs} h_{cs}(P_{it}^{NM^{std}}) + \varepsilon \tag{33}$$

Having identified π_{cs} two questions arise: How can π_{cs} be used to extend the standard noisy model and how will it be estimated. A detailed discussion of the method to estimate π_{cs} is the subject of section 4.2.3.

Abstracting from the method to determine the cost driver rate π_{cs}, the noisy model extension should value at the time of planning the demand heterogeneity for a given production program. In other words while setting the price $P_{it}^{NM^{ext}}$ the extended NM^{ext} needs to incorporate the costs of the demand heterogeneity caused by setting the price $P_{it}^{NM^{ext}}$. The demand heterogeneity for the current production program can be calculated by using eq. (31) and inserting $P_{it}^{NM^{ext}}$ into h_{cs}. The costs of the heterogeneity are reflected in the cost driver rate π_{cs}. These costs reduce the estimated profit of the profit function known from the NM^{std}:

$$\max_{P_{it}^{NM^{ext}}} \sum_{t=1}^{T}\sum_{i=1}^{I}(P_{it}^{NM^{ext}} - v_i - ABC_i\ )(A_{it} - b_i P_{it}^{NM^{ext}}) - \pi_{cs} h_{cs}(P_{it}^{NM^{ext}}) \tag{34}$$

$$\text{subject to} \quad (A_{it} - b_i P_{it}^{NM^{ext}}) \geq 0 \quad \forall i, t$$

$$P_{it}^{NM^{ext}} \geq 0 \quad \forall i, t.$$

Based upon Homburg (2004), p. 339

Eq. (34) illustrates the extended noisy model NM^{ext}. As discussed in section 3.7, the heuristics tend to systematically underestimate full costs. This error is overcome in the NM^{ext} by limiting the profits using sticky-costs factor equaling $\pi_{cs} h_{cs}(P_{it}^{NM^{ext}})$.

4.2.3 Information & simulation flow and data

To wrap up the previous sections, the steps to calculate the extended NM^{ext} are:

1. Calculate the BM^{ext} & NM^{std}
2. Estimate the cost driver rate π_{cs} based on step 1
3. Calculate the NM^{ext}

The common thread running through the simulation is almost the same as in chapter 3; first the benchmark system is simulated followed by the noisy models.

The combination of market and production parameters has been kept equal to the former simulation. The total of parameters still yields 864 BMs, whereas the number of model variations for each of the 864 BMs has been inclined to have a broader information base for the regression. Additionally in comparison the former simulation used 10 model variations per parameter combination, this time 40 variations are processed - resulting in 34,560 BM observations.

Since the focus of this research is no longer on the heuristics only, the set of heuristics has been minimized, leaving only the random and correlation size method on the first stage and big pool as well as the average heuristic on the second stage. Since the number of activity pools has a monotonic relation to the delta in profits, for this approach only 3 levels of activity pools are used. This gives a total of 12 models (2 heuristics1 * 2 heuristics2 * 3 ACPs). Figure 11 provides an overview of the simulation flow, illustrating also the regression approach being outlined in the following.

Let us focus on step 2 (see above). Basically a regression approach (the regression function is defined in eq. (33)) is used to determine the cost driver rate π_{cs}. For simplification reasons - up to this point - it was abstracted from the method to calculate the cost driver rate π_{cs}. To restate: the cost driver rate reflects the structural error a set of standard NM^{std} generates, by neglecting demand heterogeneity and cost-stickiness. The set of NM^{std} is defined by identical variable outputs and usage of heuristics. Hence for this set, π_{cs} quantifies how severe the demand heterogeneity is undervalued. The set of NM^{std} encompasses capacity cost differences (ΔC) between a BM^{ext} and a number of NM^{std}, as well as the demand heterogeneity (h_{cs}) for each NM^{std}.

Finally, π_{cs} is calculated using a linear regression between ΔC and the heterogeneity driver h_{cs}. As data points, the results from the standard (32) noisy models are used, across identical heuristic combinations and activity cost pools using the 40 simulation runs. The hereby estimated π_{cs} is subsequently used in the extended NM^{ext} noisy model to estimate $PF^{NM^{ext}}$.

The following example should clarify the approach:

1. First choose a type of NM^{std} definition: hold the choice of heuristic combination (random + average) and the number of activity pools (3 pools) static.
2. For market and production parameters choose static parameters, e.g. a decreasing market, resource cost vector level eq. 0.5, etc. This yields comparable variable outputs and distributions.
3. Use the resulting 40 BM^{ext} and NM^{std} combinations to estimate π_{cs}.

Figure 11: Information and simulation flow (2nd simulation)

$$\Delta PF_s^{NM^{std}} = PF_s^{BM^{ext}} - PF_s^{NM^{std}} \quad * \tag{35}$$

$$\Delta PF_s^{NM^{ext}} = PF_s^{BM^{ext}} - PF_s^{NM^{ext}} \quad * \tag{36}$$

Simulation	Input		Process	Output
	1. Variable costs variance (VCV, *2 level*) 2. Variable costs (*2 level*) 3. Resource cost variance (RCV, *3 level*) 4. Resource costs (*2 level*) 5. Measurement error (*3 level*) 6. Market growth (*3 level*) 7. Resource sharing (*4 level*) $\Rightarrow level^{factor}$ $= 2^3 3^3 4^1$ $=$ 864 combinations	Standard	1. Optimize profit extended benchmark model, see eq. (29). $\Rightarrow$ 40 samples 2. For each BM^{ext} calculate profit std. noisy model see eq. (30) for a combination of a. Heuristics 1 (2 level) b. Heuristics 2 (2 level) c. ACP (3 level) $\Rightarrow level^{factor}$ $= 2^2 3^1$ $= 12$ combinations	$\Rightarrow$ $\Delta PF_s^{NM^{std}}$ $\Rightarrow$ $\Delta PF_s^{NM^{ext}}$ $S =$ BM*NM $=$ 864*40*12 = 414,720
		Extension	3. Out of these 480 BM^{ext}/NM^{std} data points, calculate for each NM^{std} configuration the 40 capacity cost differences (ΔC) and demand heterogeneity (h_{cs}). 4. Using this subset asses the cost driver rate π_{cs} by means of a linear regression, see eq. (33). 5. Optimize the profit NM^{ext}. 6. Repeat steps (3) to (5) for each NM^{std} configuration (12 times).	

*$s \in S$ (simulation runs), own depiction.

Finally, as in the standard simulation of chapter 3, the obtained prices are used to calculate the corresponding profit errors, by using them in the BM as input variables and calculating the respective truly needed capacities. This is also an identical procedure as in the standard simulation used in chapter 3.2.

In total this approach yields - by combining the 34,560 BM with 12 NM combinations of heuristics and cost pools - 414,720 observations. As in the previous chapter the optimization sometimes timed out, or no optimal solution was found, resulting in 348,000 observations (84% of the 414,720 possible observations) in total.

4.3 Hypothesis Development

At the beginning of chapter 4 the basic research questions and motivation has been introduced. A central question is, if the enhanced noisy model (NM^{ext}) is able to yield higher profits than the ordinary noisy model (NM^{std}) and if so, how great is lever of the enhanced approach. Homburg (2004) has already shown that the higher level cost driver is able to enhance the ABC performance. In theory, taking the results of the former simulation model into account, it is indicated that NM^{std} performance is highly correlated with product and demand heterogeneity: Looking again at Table 13, it can be deducted that resource sharing and market growth have the first and third biggest effect on the profit error. As discussed in the "Based upon Balakrishnan and Sivaramakrishnan (2002), p. 12.

Aside from these changes the extended benchmark model follows the mechanics of the BM of chapter 3. Over a planning horizon of $t=1,\dots T$ periods the BM^{ext} optimizes prices and capacities simultaneously for products $i=1,\dots,I$ and resources $j=1,\dots,J$.

The NM adjustment" section, the NM^{ext} is designed to counter these profit decreasing effects. Hence (H1) is defined as follows:

(H1) *The extended noisy model outperforms the standard noisy model*

In addition, as discussed, the introduced driver takes the portfolio decision into account. The Heuristics on first- and second-stage are not changed in their implementation. Therefore the performance of both heuristics should not be affected, and hence the prediction is:

(H2) *The performance of heuristics on first- and second-stage is comparable between both noisy models*

Lastly, since the new driver aims at better portfolio decisions, the differentiation of the product error into its four parts should indicate that DE and KE errors differ between both noisy models. As cost allocation on portfolio level should also lead to a better resource handling of the extended model, the CE error should be lower in the extended model.

(H3) *The extended model reduces DE, KE and CE in comparison to the standard noisy model*

4.4 Research framework: Key metrics and analysis method

The basic research setting is equal to chapter 3.4, including the definition of profit errors. The fundament still is an OLS regression, which will be presented subsequently. In addition a new metric is used in the descriptive section to compare the performance of the noisy models against each other.

4.4.1 Variance of Profits

This metric is used to capture the variance of the suboptimal noisy model profits, based on Labro and Vanhoucke (2007).[132] The reference of this method is the maximum difference between noisy and benchmark model.

[132] Labro and Vanhoucke (2007) (p. 953) use this metric to control for the importance of a product and its allocated costs with respect to the portfolio. As closer the metric is to 1, only a few products account for the majority of cost in the portfolio, whereas the other products can be neglected.

This difference is set in relation to the sum of all differences between the benchmark profit and the noisy models' profits:

$$Var\_PF^{NM^{std}} = \frac{\sum_{h=1}^{H}\left(PF^{BM^{ext}} - PF_h^{NM^{std}}\right)}{max_{h=1}^{H}\left(PF^{BM^{ext}} - PF_h^{NM^{std}}\right)} \tag{37}$$

$$Var\_PF^{NM^{ext}} = \frac{\sum_{h=1}^{H}\left(PF^{BM^{ext}} - PF_h^{NM^{ext}}\right)}{max_{h=1}^{H}\left(PF^{BM^{ext}} - PF_h^{NM^{ext}}\right)} \tag{38}$$

$h = 1, \ldots, 12$ indicating (2 H1 * 2 H2 * 3 ACPs)
$n = 1, \ldots, 34{,}560$ indicating the number of BM

4.4.2 Regression Specifications

In contrast to chapter 3.4.2 the regression models slightly differ from each other. Three different regression results are compared, (39) the environment and production parameter influences on the BM, (40) in addition to these parameters, the cost system design choices on both noisy models and (41) the impact of the new driver on the extended noisy model:

$$\begin{aligned} PF^{BM^{ext}} = \; & \beta_0 + \beta_1 Market\ growth_i + \beta_2 Resource\ sharing_i \\ & + \beta_3 Resource\ cost\ variance_i + \beta_4 Total\ resource\ cost_i \\ & + \beta_5 Total\ variable\ cost_i + \beta_6 Variable\ cost\ variance_i \\ & + \beta_7 Measurment\ error_i + \varepsilon_i \end{aligned} \tag{39}$$

$$\begin{aligned} \Delta PF_i^{NM^{std}} = \; & \beta_0 + \beta_1 Market\ growth_i + \beta_2 Resource\ sharing_i \\ & + \beta_3 Resource\ cost\ variance_i + \beta_4 Total\ resource\ cost \\ & + \beta_5 Total\ variable\ cost_i + \beta_6 Variable\ cost\ variance_i \\ & + \beta_7 Measurment\ error_i \\ & + \beta_8 ACP_i + \beta_9 Heuristics1_i + Heuristics2_i + \varepsilon_i \end{aligned} \tag{40}$$

$$
\begin{aligned}
\Delta PF_i^{NM^{ext}} = \; & \beta_0 + \beta_1 Market\ growth_i + \beta_2 Resource\ sharing_i \\
& + \beta_3 Resource\ cost\ variance_i + \beta_4 Total\ resource\ cost \\
& + \beta_5 Total\ variable\ cost_i + \beta_6 Variable\ cost\ variance_i \\
& + \beta_7 Measurment\ error_i \\
& + \beta_8 ACP_i + \beta_9 Heuristics1_i + \beta_9 Heuristics2_i \\
& + \pi_{cs} + \varepsilon_i
\end{aligned} \tag{41}
$$

The regression specification encompasses one coefficient per categorical variable. The variable output can be found in Appendix B; results are illustrated in Table 18.

4.5 Results

4.5.1 Descriptive Results (H3)

First of all, in comparison to the results of the simulation approach in chapter 3.5 the results in Table 17 (Panel A) indicate that both noisy models decline in overall performance. Even by reducing - in contrast to the first approach - variable as well as resource costs (see Appendix B), comparing on average the individual NM profits, there is a gap of approx. 20 million (PF^{NM} of 80 mio.[133]; $PF^{NM^{std}}$ of 58 mio.; $PF^{NM^{ext}}$ of 60 mio.). The descriptive results also show that the extended NM^{ext} on average yields higher profits, roughly 2 million. In addition, the NM^{ext} is more volatile, suggested by the first and third quantile results as by the $Var\_PF^{NM^{ext}}$, which is for almost every quantile higher than the $Var\_PF^{NM^{std}}$. These first results support hypothesis (H1), indicating that the performance of the extended noisy model is superior to the standard model.

Panel B documents the separation of the profit error for each noisy model into the four error types: product quantity error, drop error, keep error and capacity error. On first sight one might ask, how some of the key figures can be negative? Would that not imply, that the NM performs better than the BM. But this would only be the case, if the total (profit error) is negative, which it is not.

[133] See page 64.

Table 17: Profit and Profit Error Distributions

Panel A: Standard Descriptives

	Min.	**1. Quant,**	**Median**	**Mean**	**3. Quant,**	**Max.**
$PF^{BM^{ext}}$	56,378 k	104,310 k	160,802 k	179,540 k	252,675 k	379,536 k
$PF^{NM^{std}}$	-292,486 k	-1,586 k	28,798 k	57,549 k	122,811 k	320,617 k
$PF^{NM^{ext}}$	-292,487 k	-3,152 k	31,648 k	59,665 k	124,322 k	320,617 k
$Var\_PF^{NM^{std}}$	0.09	0.31	0.34	0.33	0.37	0.39
$Var\_PF^{NM^{ext}}$	0.17	0.32	0.35	0.34	0.37	0.39

Panel B: Profit Error by Type

	Profit Error	**PQE**	**DE**	**KE**	**CE**
NM^{std}	122,029 k	-36,838 k	-20,581 k	-12,027 k	191,476 k
NM^{ext}	120,108 k	-35,839 k	-4,628 k	-9,049 k	169,623 k

* Observations: 348,000, in thousands (k).

In contrast Panel B documents, that both models achieve higher sales at the costs of over proportional high capacity costs. This finding is in line with the lower performance of both NM due to the cost sticky environmental setting. Supporting (H3) all profit error types are lower in the NM^{ext}.

4.5.2 Regression Results (H1 & H2)

The focus of this section lies on hypothesis (H1) and (H2). Therefore a deeper look into the drivers of the NM performance and the related heuristics is necessary. This is achieved by using the introduced regression (see section 4.4.2). The results are illustrated in Table 18, covering the BM profit and the profit errors of the standard and extended noisy models.

Table 18: Regression Results Non-Dummy Specification incl. the extended NM

	$PF^{BM^{ext}}$	$Profit^{NM^{std}}$ $Error$	$Profit^{NM^{ext}}$ $Error$
(Intercept)	91,979,159.34***	99,078,213.67***	94,459,091.06***
	(690.59)	(161.40)	(188.58)
Market growth	104,307,246.24***	18,466,718.09***	16,143,203.91***
	(4,213.44)	(82.13)	(88.26)
Resource sharing	-3,244,638.69***	-2,774,168.08***	-2,426,465.79***
	(-136.73)	(-40.35)	(-42.39)
Resource costs variance	1,094,118.94***	-3,844,235.98***	-3,889,407.49***
	(11.26)	(-13.65)	(-16.98)
Total resource costs	-2,490.87***	2,674.71***	2,812.55***
	(-1,254.20)	(464.88)	(598.75)
Total variable costs	-8,140.47***	-3,397.68***	-3,271.41***
	(-410.04)	(-59.08)	(-69.93)
Variable costs variance	452,538.60***	18,553.31	-33,014.78
	(5.70)	(0.081)	(-0.18)
Measurement error	-141,359.70	6,747,575.75***	6,820,814.84***
	(-1.16)	(19.17)	(23.82)
ACP		-4,104,133.10***	-5,429,943.91***
		(-146.69)	(-238.53)
Heuristics1		-5,465,248.36***	-1,251,959.70***
		(-47.52)	(-13.38)
Heuristics2		-28,404,768.17***	-27,433,893.62***
		(-97.46)	(-115.28)

Table 18: Regression Results Non-Dummy Specification incl. the extended NM (cont'd)

	$PF^{BM^{ext}}$	$Profit^{NM^{std}}$ Error	$Profit^{NM^{ext}}$ Error
Market growth * Heuristics2		-4,507,298.45***	-4,982,185.75***
		(-31.41)	(-42.56)
cost driver rate (π_{cs})			-7,475,117.69***
			(-13.55)
Adj. R^2	0.98	0.52	0.64
Num. obs.	348,000.00	348,000.00	348,000.00
			$^{*}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The findings are in line with the descriptive results, indicating that the overall performance of the extended noisy model is superior to the standard model, by ~5% points.[134]

Also the rather poor overall performance using the basic random method and big pool (incorporated in the intercept) of both models is striking. Since the delta is greater than the $PF^{BM^{ext}}$, in both cases the NM effectively yields negative profits. This underlines the hypothesis (H1) that the extended system outperforms the standard model.

The outlined results also in favor of H2 – heuristics perform equally in the standard and extended model - since the whole cost system design yields comparable results across both NM models: The heuristics on stage two, as well as the activity cost pools and the measurement error are on the same level.

[134] The relative performance is measured by dividing the profit error by the extended BM profit ($\frac{PF^{NM^{ext}}}{PF^{BM^{ext}}}$~1,0772; and $\frac{PF^{NM^{std}}}{PF^{BM^{ext}}}$~1,027;) using the intercepts.

The only real outlier are heuristics on the first stage. This result can be interpreted as the minor relevance of these heuristics because of the portfolio driver. Since the first-stage heuristic is responsible for the allocation of costs to activities, wrong cost allocation is healed on the portfolio level by the sticky cost driver rates and the heterogeneous driver (h_c). The slightly bigger effect of the number of activity cost pools could be traced back to eq. (32): Activity costs have a direct impact on ΔC and subsequently cause a "double effect" (indirectly via the sticky costs π_{cs} and directly in eq. (33)) on the extended model results.

Overall the results also suggest, that the model extension works as designed: One reason to incorporate the new driver was to improve the noisy models' robustness against changes in market situations. This is supported by the less important influence of (approx. 2 million) market growth on the delta profits. In addition the sticky cost driver rate reduces the profit error (NM^{ext}) essentially by approx. 7.5 million. However it needs to be stated, that the highest impact on profit errors lies with the usage of more sophisticated second-stage heuristics (i.e. the usage of the average instead of the big pool method). In contrast to the 7.5 million gain of the sticky drivers, advanced second-stage heuristics alone account for a lever of approx. 27.5 million, not incorporating the interaction effect between better second-stage heuristics and changes in market growth.

4.5.3 The influence of cost structure

Even if not directly comparable in absolute terms, but in direction, the simulation results of chapter 3 and the sticky simulation differ essentially. Whereas in the non-sticky simulation mainly the production parameters drove the performance of the models (resource sharing had the biggest effect), the sticky model is driven by the cost system design choices and market growth (accounting for the top 5 performance drivers only subsequently followed by production parameters).

The higher effect of cost system related influences goes along with the design of the economic environment. Prior decisions on capacity have a higher persistence, and hence changes in cost allocation have ceteris paribus a higher impact on profits. In addition costs are less controllable over time, since a decline in capacity is costly due to adjustment costs. Hence the cost structure becomes more important in a sticky environment, and has, as the results indicate a higher impact on profits.

Balakrishnan, Labro and Soderstrom (2014) discuss in their work "Cost Structure and Sticky Costs" the influence of cost structure (neglection) on prior research results. They argue, that in the data samples used to measure cost stickiness, especially in the approach by Anderson, Banker and Janakiraman (2003), costs of resources are incorporated which are only partly or not at all adjustable over the considered time horizon. Whereas the assumption of their used metrics dictates that all costs need to be fully adjustable.

While the simulation study in this chapter is far from fully incorporating these raised concerns, it also outlines the dependency of the profit realization on the underlying cost structure and supporting the raised concern by Balakrishnan, Labro and Soderstrom (2014).

4.6 Discussion of the limitations of the new approach

One may argue that even if the NM^{ext} yields higher profits, to calculate the costs of the demand heterogeneity, one needs the optimal capacity decision of the BM^{ext} and the NM^{std} pricing decisions and therefore the approach would be artificial.

Simulations analyzes are artificial by heart, but never the less able to give answers to practical questions[135]: The idea is to outline the inefficiencies by neglecting the cost-stickiness effects in planning decisions. Moreover, the aim is to introduce a basic fundament of how cost-systems need to be refined to be able to control for cost-stickiness.

Whereas the presented simulation approach is able to answer the design question, the above mentioned criticism points at the practical implication. By abstracting from the given approach a possible practical modeling

[135] See Harrison et al. (2007), p. 1243.

alternative could be measuring the information on demand heterogeneity and its inherent costs by an ex-post analysis of cost-systems. It is therefore possible to analyze planed and used capacity and their adjustment costs. Hereby a sticky factor as the heterogeneity cost driver rate can be estimated. Even an ex-ante analysis is possible, extrapolating the ex-post information to future periods. Hence a practical relevant implementation is possible. The simulation results underline, that this course of action could be profitable, because of more reliable profit forecasts.