Power of volume and price incentives in health plan payment models: A country comparison

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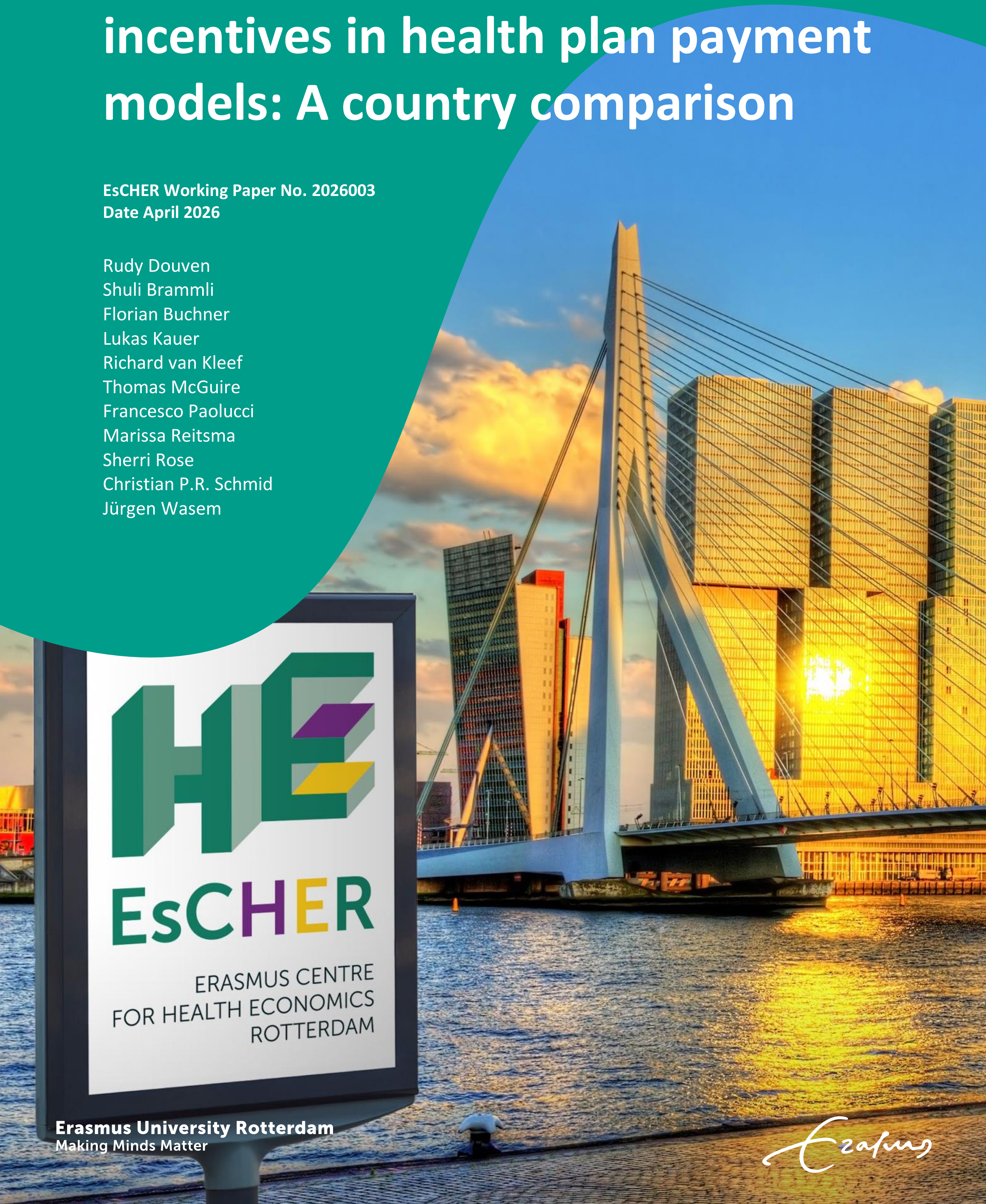

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Power of volume and price incentives in health plan payment models: A country comparison

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Abstract

In many individual health insurance markets operating under managed competition, health plans are paid by risk-adjusted capitation, sometimes combined with reinsurance and other risk-sharing mechanisms, to mitigate potential plan incentives for risk-selection. Reductions in risk-selection incentives, however, come at at a cost. Health plan payment formulas include so-called "endogenous risk adjustors," such as diagnostic indicators related to a hospital stay or an outpatient encounter, which dilute a plan's incentives to control costs. Following the contracting literature, the "power" of a health plan payment model refers to the degree to which a plan retains incentives to control cost. We propose a new empirical indicator to measure power. Furthermore, we demonstrate that power varies between two general cost control strategies employed by health plans: volume-based and price-based strategies. We assess power associated with hospitalizations for diabetes in the Dutch health insurance system and in Medicare Advantage in the US. For both countries, the risk adjustment formula cuts power about in half. We also compare power at an aggregate level for six countries. More "advanced" payment systems, which utilize many and sophisticated risk adjusters, also further reduce the incentives for cost containment and for improving efficiency.

JEL classification: H42; I11; I13; I18

Keywords: Health insurance; Risk adjustment; Efficiency; Cost control

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Disclosure statement

Each of the authors declares that they have no relevant or material financial interests related to the research described in this paper.

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1. Introduction

Many individual health insurance markets operate under managed (or regulated) competition among health plans (such as health insurers, sickness funds, or HMOs) that charge community-rated premiums to their enrollees. Examples of such markets include Germany, the Netherlands, Switzerland, and Medicare Advantage in the United States. These health plans are typically funded through risk-adjusted capitation payments, often supplemented by reinsurance and other payment mechanisms. The main idea behind these payment systems is to reduce possible risk-selection activities by health plans, thereby improving efficiency and fairness of health insurance markets (Enthoven, 1988; Van de Ven and Ellis, 2000).

The majority of the literature on health plan payment focusses on reducing potential risk-selection activities of health plans by improving the match between payments and expected costs (e.g., Van de Ven and Ellis, 2000; Breyer et. al., 2012; McGuire and Van Kleef, 2018). Risk-adjusted capitation is a payment model that attempts to draw funds from low-risk individuals to subsidize high-risk individuals in such a way that minimizes health plans' incentives to avoid individuals with predictable losses (or to recruit those with predictable profits). To predict individual spending, payment models use individual characteristics such as exogenous risk adjusters (e.g., age, sex, region) and endogenous risk adjusters (e.g., (prior) use of hospital care or pharmaceuticals). To assess the performance of the payment system numerous measures of fit have been applied in the literature, such as R^2, MPE (mean prediction error), Cumming's prediction measure etc. Van Veen et al. (2015) identified no less than seventy-one unique measures-of-fit.[1]

In addition to subsidizing high-risk individuals, capitation payments intend to convey incentives for cost control. The idea is that a budget based on a prospective payment requires

[1] European researchers tend to measure incentives to select using group-level over and under compensation measures, whereas U.S.-based researchers use predictive ratios for the same purpose. Across all research, the simple R^2 remains the most commonly reported measure of statistical performance.

the health plan to bear the cost of services provided at the margin, motivating the plan to control costs (Van de Ven and Ellis, 2000). But in fact, in virtually all payment models, health plans do not bear all the costs, as health plans receive payments from third parties, such as a sponsor or individuals. For example, if a member of a health plan consumes certain drugs, the health plan does not bear the full costs of the drugs because the plan may receive additional (risk-adjusted) subsidies from a sponsor or copayments from the individual that (partially) offset these costs. The concern is that a health plan might be more lenient in allowing health care providers to prescribe these revenue-generating drugs, and less willing to steer health care providers to search for cheaper substitutes (see Van de Ven, Van Vliet and Lamers, 2004). The payer/regulator thus faces a tradeoff: improving the performance of the payment system in terms of reduction of incentives to select risks by including additional risk adjusters may weaken health plan incentives for cost control (Newhouse, 1996; Eggleston, Ellis and Lu, 2012; Geruso and McGuire, 2016).

While the point that health plan payment models can dilute incentives for cost control is generally accepted, there is no standard measure in the literature by how much incentives are diluted. Extreme cases are understood. At one side of the continuum, in a fully prospective payment model payments to health plans depend only on risk factors such as age and sex independent of service use. In this model, health plans are strongly incentivized to control costs by encouraging providers to do the same, since service utilization and plan expenditures do not impact revenues. At the other side of the continuum, in a cost-based payment model, all costs are recovered in revenues. In this extreme case, a health plan has no incentive to stimulate providers to control cost. In practice, health plan payment models fall in between, with revenues depending partly on use and partly on non-use-based risk adjusters. Revenues may further depend on risk-sharing mechanisms where payments are based on actual costs, as with reinsurance. Another form of risk-sharing is demand-side cost sharing (e.g., copayments, deductibles, coinsurance) that play into plan incentives as well. To the degree that costs are shared with individuals, savings from cost control go to individuals, not to the plan. The inclusion of various risk adjusters and risk-sharing mechanisms makes the quantification of cost-control incentives in practice highly complex.

The paper aims to shed light on quantifying power, that is, to characterize and compare the strength of incentives for health plans to engage in cost-control activities in actual payment models. We build our framework along the lines of Geruso and McGuire (2016) who follow contract theory (e.g., Laffont and Tirole, 1993) and introduce the concept of power of a payment system. Laffont and Tirole (1993) explain that power is maximized with a fixed-price contract (corresponding to a payment to a health plan independent of current or past utilization) and decreases as the price is tied to realized costs. In health plan payment, power falls as the payer compensates health plan expenditures on the margin.

Our contribution is to define a new power measure that, in contrast to Geruso and McGuire, it is more intuitive, as it reflects the perspective of the entity performing the activity—the health plan. Health plans primarily focus on the overall results, costs, and revenues of enrolled individuals at the plan level, rather than on the power values of individual enrollees. It has the additional advantage that in some specific cases a power measure requires only a small number of data elements that may be publicly available. We illustrate our calculations based on the plan payment systems in six countries.

Incentives for cost control differ across types of services or disease categories. We assume that health plans have measures to control provider costs to some extent, but the degree of control varies by condition and service. We derive our power measure by comparing the risk-adjusted payments for a group of individuals with a condition/service use to the payments the same group would have generated for the plan had members of the group not had the condition and received no services for its treatment. We compare the difference in revenue in payment to health plans between the group in both states to the difference in costs for these condition. For example, to characterize the power of a health plan activity that stimulates providers to reduce hospitalizations for a group of patients with diabetes care, we compare the costs of a hospitalization for diabetes to the increment in revenue a plan receives due to the hospitalization. We measure power for the average individual in the group.

We further contribute by distinguishing two general forms of cost control strategies of health plans, a volume-based and price-based strategy. An example of a volume strategy is to incentivize providers to restrict service use, such as hospitalizations, or to prescribing alternative drugs for specific treatments. An example of a price strategy is negotiating lower prices with providers for a subset of claims. Power will differ for both types of strategies when health plan payment systems distinguish between cost- and volume-based risk adjusters or when risk-sharing mechanisms are present. Cost-based risk adjusters are affected by both, changes in price and volume, while volume-based risk adjusters are affected only by changes in volume. In section 3, we demonstrate how power values can be calculated for activities related to diabetes, for Medicare Advantange in the US and for the health insurance system in the Netherlands.

In addition to service or condition-based comparisons, we compute a comparable overall power measure for plan payments in six countries: Australia, Germany, Israel, Medicare Advantage in the US, the Netherlands, and Switzerland. These power measures provide insights into the use of cost-based and volume-based risk adjusters, and other risk-sharing mechanisms across countries. We construct this measure by assuming that a health plan can eliminate all volume (or setting the price of use to zero) for one "average" enrollee, while holding every other person's use (and prices of use) fixed. Our results indicate that there are large differences across countries. Average power of volume incentives (i.e., the share of costs at the margin borne by a plan) range between around 0.34 and 0.80, while average power of price incentives range between 0.55 and 1.00. These results can be interpreted as follows. If power is 0.55, a health plan, that saves one euro, keeps 55 cents and the remaining 45 cent of savings are redistributed to third parties (the sponsor, other insurers or enrollees).

It is important to note that a power indicator measures *incentives* related to health plan payments, and not the *response* of health plans to incentives. In practice, the implementation of cost-control strategies by health plans depends on additional considerations, such as the effort and investments that are needed to perform a cost-control strategy, and the assessment that a strategy will be successful.

2. Price and volume incentives in health plan payment systems

A health plan payment system is a key element of regulated competition in individual health insurance markets, where the regulator designs a benefit package and constructs a payment system to pursue objectives associated with access, affordability, and efficiency (Van de Ven and Ellis, 2000). A payment system specifies how the revenue of health plans is determined. In practice, the revenue may come from various sources, such as premiums, subsidies or capitation. A payment system can generally be represented as follows:

$$R(i) = \sum_j \alpha_j X_j(i) + \sum_k \beta_k X_k^{use}(i) + f(C(i)), \qquad (1)$$

where $R(i)$ is the payment a health plan receives for individual i. The first two terms on the right-hand side are sets of indicator functions and represent two different types of risk adjusters in a capitation system, while the third term corresponds to risk-sharing mechanisms coming from the regulator or individuals.

The first term, $X_j(i)$, relates to a set of j *exogenous* risk adjusters, characteristics of individual i that are exogenous with respect to an individual's health care utilization or costs, and cannot be influenced by health plans. Examples include age, sex and geographical region.

The weights α_j determine the payment a health plan receives for an individual with a given set of exogenous characteristics. In practice, these weights are typically estimated with least-squares regressions. We take these weights as given. In other words, a health plan receives at least $\sum_j \alpha_j X_j(i)$ for individual i, irrespective of health care use and costs.

The second term, $X_k^{use}(i)$, relates to a set of k *endogenous* or use-based risk adjusters, flagged only if individual i utilizes certain health care. The weights β_k determine the payment related to the specific risk adjuster triggered by that usage. Examples of use-based risk adjuster include pharmaceutical consumption or diagnoses received during hospital care. These risk-adjusters can depend on utilization or costs of individual i. A health plan receives additional compensation based on these risk adjusters. They are termed *endogenous* risk adjusters because, at the population level, a health plan can influence the occurrence of health care use.

The third term, $f\big(C(i)\big)$, refers to (ex-post) *risk-sharing* in plan payment. Risk-sharing means that after the costs $C(i)$ are realized for all individuals i, the regulator or another third party pays $f(C(i))$ to the plan for individual i. Note that $C(i)$ is the total health care costs related to the services of the benefit package, not just the costs for which the plan is responsible. The $f\big(C(i)\big)$ term could be used to represent reinsurance or proportional risk sharing. Risk sharing, like risk adjustment, improves fit and can mitigate problems related to risk selection (McGuire and Van Kleef, 2018). However, we concentrate here on the fact that risk sharing also affects incentives for cost control. To illustrate a power calculation with respect to risk sharing, suppose reinsurance stipulates that all costs above 50k for an individual will be fully reimbursed by the regulator. Then the function of plan payments in terms of costs is: $f(C(i))$= 0 if $C(i)$ < 50k; $f(C(i))$ = $C(i)$–50k if $C(i)$ > 50k. In this example a plan has no incentives to control costs above 50k€ and the overall power of a payment system with reinsurance will depend on the frequency with which costs exceed 50k. The $f\big(C(i)\big)$ term also includes demand-side cost-sharing that affects incentives to the plan to control costs. To illustrate, suppose individuals are responsible for a 20% coinsurance for all health care costs. If a plan member spends 1€ on health care, the plan is responsible for only 0.80€. The 20% coinsurance by itself reduces the power of the health plan payment system from 1.00 to 0.80.

In sum, in health insurance contracts, power reductions in relation to a fixed capitation payment contract come from the *endogenous* risk adjusters in the ex-ante risk-adjusted capitation system and from the *risk-sharing* mechanisms by third parties.

2.1. *Measuring power associated with activities by health plans*

An important goal of regulated competition in health insurance markets is to convey incentives to a health plan to control costs. Health plans can undertake many activities to deliver care at lower cost. Some examples are negotiating lower costs for health services or directing patients to lower-cost providers, preventive care activities that improve health and lower long-term costs, and utilization management, such as requiring authorization for certain procedures or medications etc. Health plan activities are often targeted to a group of individuals with a certain disease or condition, and are intended to change health care use and costs for this group of patients. The main idea behind the concept of power is that *any* activity exercised by a health plan may potentially change the revenue in payment $R(i)$. Our approach is consistent with economic models of profit-maximizing health plans that decide about resources to be made available to enrollees at the level of a service (e.g., cardiac care). (Layton *et al.*, 2018)

Geruso and McGuire (2016) (GM in what follows) assessed power with respect to a form of "marginal cost" by eliminating a small random subset of utilization from a claims data set and applying the payment formula to the modified data. Costs fall and revenues fall. Power in GM was defined as one minus the fall in revenues over the fall in costs. For further details see Appendix A.

GM construct their power measure by averaging power measures for each individual seperately. In contrast, we start from the observation that health plan activities are often targeted to groups of individuals, for example with a certain disease. Because risk adjusters, corresponding weights, and risk-sharing mechanisms in $R(i)$ may depend on the type and costs of the disease in a payment model, the incentives for cost control might differ markedly between diabetes care and cancer care, for example.

To characterize power for a cost control strategy related to a group of individuals with disease d, we eliminate the corresponding costs of treatment for the disease for these individuals in the plan and compare the cost reduction to the revenue reduction in payment according to the health plan payment formula. Power is lower when the revenue fall is large in relation to the fall in costs.[2]

Let C_d be the total costs of treatment that are related to disease d and impacted by the health plan's cost control activity. Let R be the actual revenue of the health plan, and $R_{\sim d}$ be the revenue to the plan after treatment costs for disease d are eliminated. Power of incentives for the health plan activity related to disease d can then be defined as:

$$P_d = 1 - \frac{(R - R_{\sim d})}{C_d} \qquad (2)$$

When plan revenue are unchanged with respect to elimination of costs of treating disease d, $R = R_{\sim d}$ and power $P_d = 1$. The plan is the recipient of all the cost savings and has strong incentives to apply this cost control strategy. If, on the other hand, revenues fall substantially when costs of d are eliminated, power is reduced and a plan has less incentive to apply this control cost activity. For example, a fall in the magnitude of demand-side cost sharing obligations with the elimination of costs for disease d also implies lower power. Reductions in demand-side cost sharing represent cost savings to individuals not to the plan.

[2] Note that throughout the document we adopt the "all else equal" assumption. Specifically, we assume that marginal activities do not alter (future) payment schemes and do not trigger responses from other players.

It is even possible that $P_d < 0$. Negative incentives for cost control occur when the loss in revenue of the cost control strategy exceeds the costs associated with treatment, i.e. net revenue $(R - R_{\sim d}) - C_d > 0$.

For instance, this situation can occur when a prevention activity prevents the occurrence of a disease that receives a high weight from a risk adjuster in the payment system. Also, when there are multiple diseases within a risk adjuster, the weight can be relatively high for inexpensive diseases. In such cases, the weight assigned may exceed the average cost of the disease itself. Another example involves a disease covered by a risk adjuster with weights based on costs or use thresholds. If a cost-control activity reduces the costs of the disease from just above to just below a threshold, the resulting cost savings related to the treatment may be small compared to the loss in payment revenue. This example mirrors the incentives of upcoding, where a plan increases its revenues by "upcoding" a treatment to above a threshold of a risk adjuster (Geruso and Layton, 2021; Politzer, 2024).

The example of prevention activities raises the question of how we regard the timing of costs and revenues to happen in our analysis (Eggleston, Ellis and Lu, 2012, Weinhold et al., 2019). In practice, it is common in prospective risk-adjustment systems for costs associated with a hospitalization to occur in year 1 whereas the revenue consequences come in year 2. The Dutch payment model references costs up to three years in the past to determine payment in the current year (Van Kleef et al., 2018). Here, we simply bring all present and future revenue effects related to the activity forward to the same period in which costs are incurred.[3] This, in effect, assumes also that enrollees stay with a plan so that the plan bears the fruit of any positive revenue effects of its spending.[4]

[3] This allows us to quantify the overall effect of an activity and enables a fair comparison among different types of models, including concurrent and prospective models (with various lags).

[4] A disenrollment rate for any reason, including death, could be included in our formula for power, but because our main objective is comparison across activities, we keep the emphasis on the connection between costs and revenues in the payment model.

Our concept of power is not confined to cost-control strategies. It can also apply to efficiency activities of health plans—for example, consider an activity by a health plan that authorizes providers to invest in costly new technologies to improve the quality of care. These activities become more attractive to a health plan when power is low, as health plans receive higher revenues from the payment system. Conversely, when power is low, the financial incentives for health plans to invest in preventive care may also decrease, since cost savings from prevention can lead to a reduction in future payments under risk-adjusted models.

Appendix A outlines the differences between our power indicator and GM's. Unlike GM, we can, in some cases, calculate power even when individual claims are unavailable. For example, power in (2) can also be applied to an activity that affects all diseases at once, answering the empirical question of what a plan payment system implies for the average power. We calculate this aggregated measure of power with publicly available data on our six countries, and discuss its interpretation in section 4.

2.2. *Power of volume and price incentives*

The strength of incentives differs according to whether a health plan adopts a price or volume activity. This distinction between power of *volume* and *price* provides information about incentives a health plan has to pursue a volume versus price strategy to contain costs. The difference exists because, in general, the *endogenous* risk adjusters in (1) may derive from either *volume* or *cost* data. To explain this difference, we split $X_k^{use}(i)$ into two terms:

$$R(i) = \underbrace{\textstyle\sum_j \alpha_j X_j(i)}_{\substack{\textit{No effect on} \\ \textit{incentives for} \\ \textit{cost-control}}} + \underbrace{\textstyle\sum_l \beta_l X_l^{volume}(i)}_{\substack{\textit{Effect on volume} \\ \textit{incentives only}}} + \underbrace{\textstyle\sum_m \gamma_m X_m^{costs}(i)}_{\substack{\textit{Effect on price} \\ \textit{and volume} \\ \textit{incentives}}} + \underbrace{f(C(i))}_{\substack{\textit{Effect on price} \\ \textit{and volume} \\ \textit{incentives}}} \tag{3}$$

$X_l^{volume}(i)$ represents volume-based risk adjusters, which contain only information about treatment volume of individual i, and X_m^{costs} represents cost-based risk adjusters, which contains only information about the costs of individual i. A volume-based cost control strategy, for instance, prescribing fewer drugs or reducing the number of services, will impact both the treatment volume *and* its associated costs, potentially affecting the last three terms in (3). In contrast, a price-based strategy, such as reducing the price of a drug or a service, may impact the costs but not the utilization of the drug. A price-based strategy will therefore only influence cost-related risk adjusters, the last two terms in (3).

Finally, we do not consider any long-term or market-wide effects of a change in service use or price. We neglect any impact on estimated payment weights or on any other prices or utilization.

3. Empirical illustration of power indicators

In this section, we calculate the power for a specific health plan activity related to diabetes mellitus. Diabetes is a chronic illness treated by medication, outpatient health care, and hospitalizations. Diabetes can lead to various complications, heart disease and stroke, nerve and kidney damage. Diabetes has a high prevalence and high costs (Patel, 2025). We measure the power for two cost-control activities that a health plan can pursue for diabetes. In section 3.1, we focus on preventing hospital treatment (see, e.g., Zhou et. al., 2020). In section 3.2, we study lower hospital prices for diabetes.

As empirical exercises depend on data availability, we examine this activity for the Netherlands and Medicare Advantage (MA) in the US. For both countries, we utilize cost data on individual hospitalizations and risk-adjusted payment information. We assume the health plan serves an average population in terms of health risks and other characteristics.

First, we provide a short summary of the Dutch and MA risk adjustment systems that were operational in 2023 and 2020, respectively. In our simulation, we apply these models to cost data from 2020. In our summary below, we also highlighted the role of diabetes. In Appendix B, we provide additional information about both payment systems and the power calculations.

In the Netherlands, about 6.6% of the total Dutch population is recognized as having diabetes.[5] About three-quarters of this population had hospital costs, with an average of total (inpatient and outpatient) hospital costs of 4,663 euros.[6] The Dutch risk-adjustment model is prospective and makes use of a volume- and cost-based risk adjuster relevant to diabetes. The volume-based risk adjuster, known as diagnostic cost groups (DCG), comprises twenty-six categories. Individuals are assigned to a DCG-category, such as diabetes, on the basis of their hospital claims in the previous year. In 2020, about 43% of the diabetes population was assigned to one or more DCG categories. The cost-based risk adjuster, referred to as multiple-years high-cost groups (MHC), comprises eight categories. Individuals are assigned to an MHC-category if their total health care costs in the previous three years were relatively high. In 2020, about 85% of the diabetes population was assigned to a MHC category.

For the US, we study the MA payment model and apply this model using data from individuals in Traditional Medicare. Medicare covers people aged 65 years or older, of whom about 24.4% have diagnosed diabetes.[7] The MA risk adjustment model is prospective and is based on diagnosed conditions from the previous year. Version 24 of the payment model, which we use for our analysis, has 86 volume-based hierarchical condition categories (HCC) and no cost-based categories. For the group under study, patients hospitalized for diabetes, the average risk score is 3.3, considerably higher than the population average of 1.0. Among the hospitalizations in 2020, 32% included a diagnosis that mapped to one of three diabetes-related HCCs (17, 18, 19), and the principal or admitting diagnosis was diabetes for 4% of all hospitalizations. The average Medicare payment for hospitalizations for diabetes was $13,500 dollars, which reflects Medicare payments to the hospital and physicians that are related to the

[5] https://www.nivel.nl/nl/zorg-en-ziekte-in-cijfers/cijfers-ziekten-op-jaarbasis
[6] Note that the Dutch data does not allow us to distinguish whether the hospitalization of a diabetes patient is related to diabetes.

[7] https://www.cdc.gov/diabetes/php/data-research/index.html, accessed on July 3, 2025.

first discharge for diabetes in 2020.[8] Note, that the Dutch and MA health plan payment systems any risk-sharing mechanism by the regulator.[9]

3.1. *Incentives for preventing hospital treatments for diabetes patients*

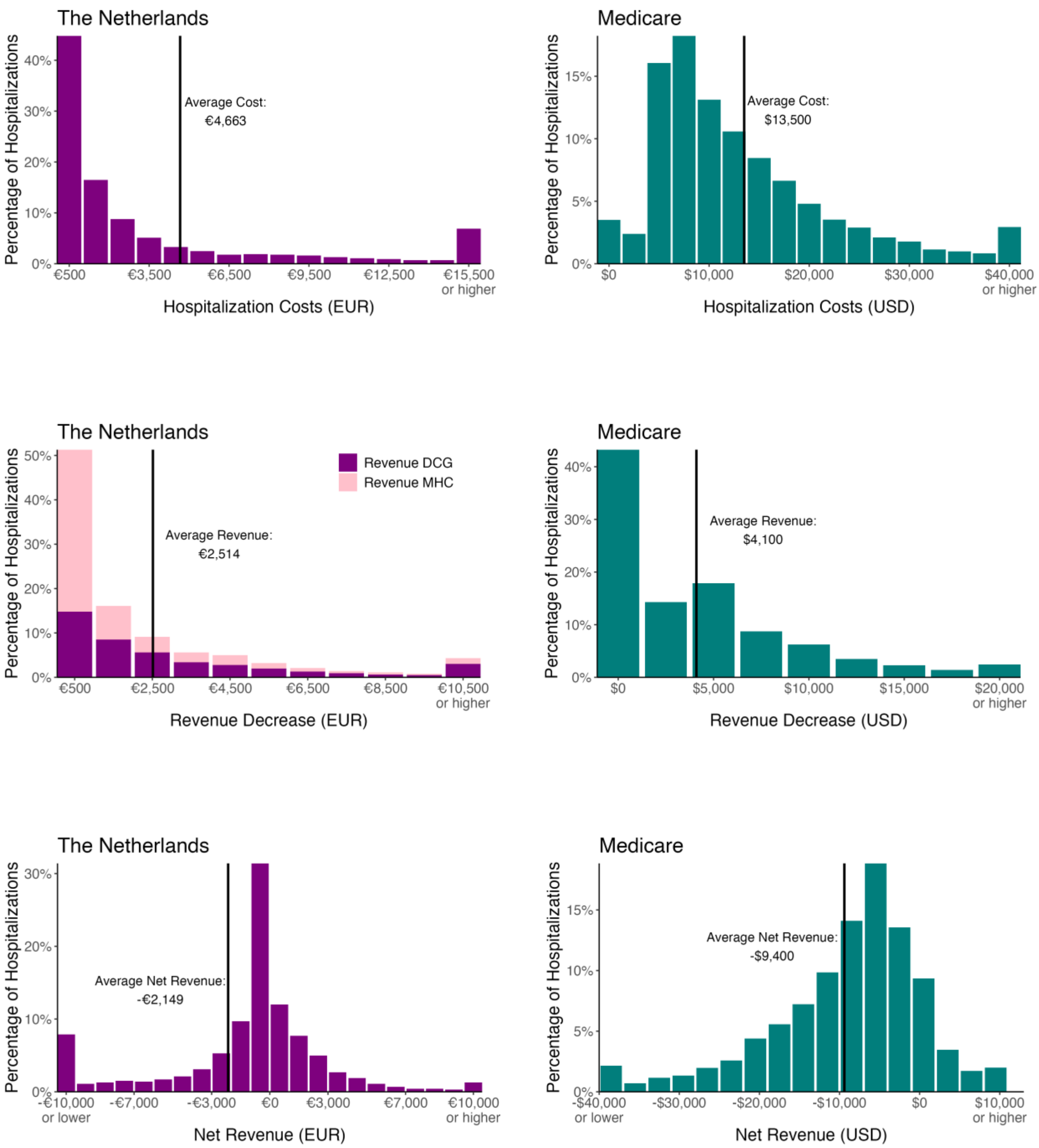
We assume that the health plan has implemented a prevention initiative aimed at avoiding hospitalizations, resulting in a random number of patients no longer requiring hospital treatment. To measure the average power associated with this activity we define group d as the entire group of diabetes patients with hospital costs. In our context of diabetes prevention, this means that we set hospital costs C_d to zero for all diabetes patients. We calculate C_d as the hospital costs to the health plan for all individuals in group d, and assume that costs related to other types of services, other than these hospital costs, do not change. For each year, we determine the revenue R related to group d directly from the risk-adjustment system, by summing up $R(i)$ of each individual i in group d. To approximate $R - R_{\sim d}$ we (re)move the flags in the risk adjustment system that correspond with the change in hospital costs, and change revenues that are contingent upon alterations in payments associated with the corresponding risk categories.

The first of the three left figures in Figure 1 shows the large variation in costs $C_d(i)$ of Dutch diabetes patients with hospital costs, which can potentially be saved by prevention activities. The second left figure shows the variation in the decrease in health plans' revenues

[8] Mean hospital costs are much higher in the US than in the Netherlands. Due to differences in data availability we had to use inpatient costs in the US and total hospital costs in the Netherlands. The latter average is lower because it contains many people with relatively low outpatient hospital costs in the population (see figure 1). Other differences might relate to the older age of the population in Medicare, and that hospital prices are considerably higher in the US (Papanicolas et al., 2018).

[9] The Netherlands has a mandatory deductible of 385 euros. However, the effects on our incentive measure are negligible as almost all diabetes patients have overall health expenditures larger than 385 euros after taking hospital costs out. Traditional Medicare requires a beneficiary to pay a deductible for an inpatient stay ($1408 in 2020). MA plans whose incentives we are interested in characterizing do not generally require significant demand-side cost sharing.

Figure 1. *Preventing diabetes hospitalizations. Distributions of hospital costs, revenue decrease, and net revenues, in the Netherlands and Medicare.*



Notes: The figures show three distributions for the Netherlands (left) and Medicare Advantage (MA) (right). The upper two figures are hospital costs C_d for hospitalized diabetes patients. For the Netherlands, this includes inpatient and outpatient hospital costs and for Medicare only inpatient hospital costs.The two middle figures show the decrease in health plans' revenues $R - R_{\sim d}$ from the risk adjustment system. For the Netherlands, the revenue decreases are related to the risk adjusters DCG and MHC, where the purple and light purple colors in the figure represent the shares of revenues. For Medicare, the revenue decrease is related to the risk adjuster HCC. The last two figures show that preventing hospitalizations of diabetes patients results in a distribution of net revenues $(R - R_{\sim d}) - C_d$. The vertical black line indicates the average of the distribution.

$R(i) - R_{\sim d}(i)$. The decrease in revenue is related to the risk adjusters, DCG and MHC. For DCGs, the change in revenue is determined by assuming that all persons in group d receive no revenues from DCGs in 2020. MHCs depend on the sum of individual total health care costs of the past three years. To obtain the change in revenue we assumed that the past prevention activity caused individual hospital cost to fall to zero for persons in group d in the past three years.

Finally, the third left figure shows the distribution of net revenues $(R(i) - R_{\sim d}(i)) - C_d(i)$. Remarkably, diabetes patients sometimes have positive net revenues, sometimes even larger than 10,000 euros. For these patients, the reduction in health plan payment is larger than the costs of hospitalization. This indicates that plans make losses when keeping these patients out of a hospital. On average, however, net revenues are $-2{,}149$ euros implying that on balance, preventing hospital treatments of diabetes patients is profitable for a health plan. Table 1 summarizes the main results. We find a power measure of 0.46 indicating that when preventing a hospitalization, a health plan keeps on the margin 46% of the reductions in hospital costs. The reduction in power in the Dutch payment model is due to lower payments from dropping the volume-based risk adjuster DCG (0.33) and from the cost-based risk adjuster MHC (0.21). Note that the sum, $0.33 + 0.21 = 0.54$, yielding our power measure $1 - 0.54 = 0.46$.

The three right figures in Figure 1 show the same distributions for the hospitalized diabetes patients in Medicare. Similar to the Netherlands, we observe a large and similar type of variation. Also in Medicare, many diabetes patients have positive net revenue, sometimes larger than 10,000 dollars, indicating considerable losses when health plans prevent a hospitalization for these patients. On average preventing hospitalization is profitable as average net revenues are negative, –9,400 dollars. This results in a power measure of 0.70 (see Table 1). Interestingly, power of incentives for keeping diabetes patients out of the hospital is higher for Medicare than for the Netherlands. Due to differences in data availability, we applied the prevention activity in Medicare to diabetes patients with inpatient hospital costs, whereas in the Netherlands to patients with outpatient and inpatient hospital costs. It is not clear a priori whether this difference, or other cost differences between both countries, leads to a higher or lower value for power, as this choice affects both the numerator and the denominator in our power equation. A contributing factor for the higher power value in Medicare may be that Medicare employs only volume-based risk adjusters and does not include multi-year high-cost risk adjusters. See Appendix B for a more detailed description of our calculations.

3.1. *Lower price for hospital treatments related to diabetes patients*

We next consider incentives to a plan to seek a lower price for hospital treatments for diabetes patients. An important difference with the previous exercise is that a price change does not affect use, and that DCG categorization in the Netherlands, and HCC categorization in MA is unaffected. A change in price solely affects a health plan's revenues that are related to cost-based risk adjusters; thus, in our exercise they only impact the Dutch MHC-risk adjusters. The bottom two rows in Table 1 summarize the outcomes of a simulation in which we virtually lowered the price of hospital care for all diabetes patients by 10%. For the Netherlands, a reduction in hospital costs results also in a reduction of the number of patients in high MHC-risk categories, and thus a reduction in plan payment. For the Netherlands, we find a power value of 0.84 indicating a reduction in power of 0.16, due to the MHC-risk adjuster. Other price reductions yield a similar power value (see Apendix A). For MA, there is no reduction in power because there are no cost-based risk adjusters or other risk-sharing mechanisms present in the MA risk adjustment model, thus power of price incentives remains at 1.00.

Table 1. *Average power values for a volume and price activity w.r.t. diabetes patients*

	$\bar{C}_d$	$\bar{R}$	$\bar{R}_{\sim d}$	$\bar{R} - \bar{R}_{\sim d}$	$\boldsymbol{P_d}$	ΔX_l^{volume}	ΔX_m^{costs}
Volume activity: Preventing hospitalizations							
the Netherlands	4,663 €	8,638 €	6,124 €	2,514 €	**0.46**	– 0.33	– 0.21
US: Medicare	13,500 $	31,200 $	27,100 $	4,100 $	**0.70**	– 0.30	-
Price activity: Lowering hospital prices by 10%							
the Netherlands	466 €	8,638 €	8,563 €	75 €	**0.84**	-	– 0.16
US: Medicare	1,350 $	31,200 $	31,200 $	0 $	**1.00**	-	-

Notes: ΔX_l^{volume} refers to the proportion change in power due to DCGs for the Netherlands and HCCs for Medicare. ΔX_m^{costs} refers to the proportion change in payments due to MHCs for the Netherlands. All numbers represent averages and are rounded. € refers to euros and $ to US-dollars.

4. An overall power indicator of price and volume incentives

The analyses of incentives related to hospitalization for diabetes demonstrates that power indicators can be calculated for specific health plan activities associated with a specific population or disease. For policy purposes, it might be informative to also have an "overall" power measure for a risk adjustment system. An overall measure for power offers insight into how alterations in the design of risk adjustment design impact power, and how overall power varies among risk adjustment systems across countries. For the calculation of overall or average power, we gathered information on risk-adjusted capitation payment systems in six countries (see Table 2). In these countries, public or semi-public aggregate data enable us to combine weights and the prevalence of all risk adjusters with total reported healthcare expenditures.

Our overall power measure considers the total treated prevalence of diseases and the entire risk adjustment system. In this exercise a health plan eliminates all volume (or setting the price of use to zero) for one "average" enrollee, while holding every other patient's use (and prices of use) fixed.

We can apply our power measure presented in (2) above, by using averages instead of totals, and choosing d as the entire population with all diseases. The mean health care expenditure per individual, $\bar{C}_d$, is calculated by dividing total health care expenditure by the size of the population. $\bar{R}$ is the mean per individual risk-adjusted payment received by the health plan and equals $\bar{C}_d$. The main part of the exercise is to divide $\bar{R}$ in five different payment categories. Equation (3) splits up $\bar{R}$ in four parts, but here we additionally split up $f(C(i))$ into two parts, a part that corresponds to risk-sharing by the regulator and a part that corresponds to risk-sharing by the consumer. These five payment categories are presented in the first column of Table 2. For our exercise, we need the share of total spending for each country of these five payments categories. We obtain this information by using, often public, information of each country's risk-adjustment system, weights, prevalence and risk sharing mechanisms (for more detailed information, see Appendix C). To obtain overall power of volume, we determine $\bar{R}_{\sim d}$ by setting the endogenous volume- and cost-based risk-adjusters, and risk-sharing mechanisms in $\bar{R}$ to zero. If all volume is set to zero, the health plan will only receive the payments related to the exogenous risk adjusters, and there will be no other payments.[10] In the case of the price exercise, we set only the cost-based risk adjusters and risk-sharing mechanisms to zero, because we assume that the average enrollees still receive the full volume of treatments, but for a zero price (and zero costs).

Table 2 presents the overall power indicator for volume and price for six countries. It shows the year of the risk-adjustment model that we used, mean health care expenditures, and the share of the payment related to each of the five categories. Overall, power of volume equals the share of payments related to exogenous risk-adjusters and overall power of price equals the share of the exogenous risk adjusters plus the volume-based risk adjusters.

Hospital private health insurance in Australia is complementary to the mandatory Medicare system. The health plan payment system, as detailed in Paolucci et al. (2018) and Henriquez et al. (2023), relies solely on risk-sharing features: an age-based pool and a high-cost claimants pool. Risk sharing amounts to approximately 45% of total healthcare spending, resulting in a

[10] Note that this assumption does not necessarily hold for all possible risk-sharing mechanisms a regulator can apply. However, it holds for the risk-sharing mechanisms we consider in this exercise.

Table 2. *An overall power measure of volume and price incentives*

	Australia	Germany	Israel	Netherlands	Switzerland	US (MA)
Year	2021	2021	2021	2021	2021	2020
Mean health care expenditures	1,428 (AUD)	3,219 (EUR)	5,314 (NIS)	2,836 (EUR)	4,077 (CHF)	9,366 (USD)
(1) Exogenous risk-adjusters	55%	43%	80%	38%	34%	55%
(2) Volume based risk-adjusters	0%	54%	4%	27%	35%	45%
(3) Cost based risk-adjusters	0%	0%	0%	28%	0%	0%
(4)Risk-sharing (regulator)	45%	3%	10%	0%	20%	0%
(5) Risk-sharing (individuals)	0%	0%	6%	7%	11%	0%
Power (volume)	**0.55**	**0.43**	**0.80**	**0.38**	**0.34**	**0.55**
Power (price)	**0.55**	**0.97**	**0.84**	**0.65**	**0.69**	**1.00**

Notes: Calculations are based on information about each countries risk-adjustment systems. All numbers represent averages and are rounded. The information about Australia, Germany, Israel, Netherlands, Switzerland and the US is publicly available. Due to differences in population and insurance coverage, mean health care expenditures can vary substantially across countries. For instance, Australia includes only the hospital private health insurance system; Germany the public health insurance system; and the United States (Medicare Advantage) covers solely individuals aged 65 and older. For more information about the calculations and a countries risk-adjustment system, we refer to Appendix C. AUD = Australian Dollar, NIS = Israeli New Shekel, EUR = Euros, CHF=Swiss Francs, USD= US Dollars.

reduction of power incentives to 55%. Because the risk-sharing mechanism is cost-based, both the overall power of volume and price incentives are equal, at 0.55.

The German risk-adjustment system refers to the public health insurance systen, as detailed in Wasem et al. (2018), consists of exogenous and endogenous risk adjusters, as well as risk sharing. In 2021, the volume-based risk adjusters consist of 495 hierarchical morbidity groups who account for about 54% of total spending. Additionally, there is risk-sharing in form of a high-cost pool reimbursing 80% of all annual individual expenditure exceeding 100.000 €, which accounts for about 3% of total spending. This results in an overall power of volume incentives of 0.43 and price incentives of 0.97.

The Israeli payment system, as detailed in Brammli-Greenberg et al. (2018), comprises 44 risk classes of risk adjusters, which are a combination of age, sex, and regional risk adjusters.

Israel has a single volume-based risk category that relies on diagnoses, distinguishing five disease classes and account for a spending share of 4% within the payment system. Risk-sharing by the government accounts for 10%, and demand-side cost-sharing for about 6% of the budget. This results in a power of volume incentives of 0.80 and power of price incentives of 0.84.

The Dutch risk-adjustment system of 2023 differentiates between various volume and cost-based risk adjusters within their risk-adjusted capitation model. The system includes four volume-based risk classifications (with 82 risk classes in total) based on prior use of hospital care, pharmaceutical care, physiotherapy and durable medical equipment. For a description of these risk adjusters, see Van Kleef et al. (2018). In terms of the payment system, these volume-based categories collectively represent a spending share of 27%. The system comprises two cost-based risk classifications (with 17 risk-classes in total) based on high spending in multiple prior years for somatic care and for home and geriatric rehabilitation care. These cost-based risk adjusters represent a spending share of 28%. Demand side cost sharing comprises of about 7%. As a result, the average power of volume incentives is $1-0.27-0.28-0.07=0.38$ and power of price incentives is $1-0.28-0.07=0.65$.

The Swiss payment system, as detailed in Schmid et al. (2018), features two volume-based risk categories. One of these risk categories comprises 1560 risk classes, with each class defined by a combination of age, sex, canton, and whether there was a hospital or nursing home stay over at least three consecutive nights in the previous year. The monetary transfers within the payment system, pertaining to this risk category, account for a total spending share of 13%. The second risk category consists of 34 pharmaceutical cost groups, representing a total spending share of 22%. Moreover, there is risk-sharing as cantons pay retrospectively on average about 55% of all inpatient costs within a canton, which is about 20% of total spending, and demand-side cost sharing of about 11%. This yields that average power of volume incentives is 0.34 and of price incentives 0.69.

The US MA payment system, as detailed in McGuire and Newhouse (2018), incorporates exogenous risk adjusters, including age, sex, and an indicator for original eligibility due to disability. In 2020, it had one volume-based risk-category with 86 HCCs, including six interaction terms between HCCs as well as indicators for the number of HCCs, with a total payment spending share of 45%. Note that in MA there is no risk sharing by a regulator or individuals. Therefore, the average power of volume (or cost) incentives is 0.55, while the average power of price incentives is 1.00.

The power indicators reveal interesting differences. In all countries, the average power of volume incentives is substantially below 1.00. In most countries, except Australia, the average power for price incentives is higher than for volume incentives. More "advanced" risk-adjusted capitation systems, which utilize many and sophisticated risk adjusters to reduce plan incentives for risk-selection also reduce the incentives for cost containment and improving efficiency. Most countries extensively apply volume-based risk adjusters. This has the advantage of only lowering power of volume incentives and not price incentives. Four of the six countries make use of cost-based risk adjusters or risk-sharing mechanisms, in many cases lowering both the power of volume and price incentives considerably. The impact of demand-side cost sharing on power is relatively small in all countries.

The overall power indicators serve as a baseline for international comparisons. However, for policy evaluation, more precise methods of measuring power would yield deeper insights. Section 3 illustrates how these assessments can differentiate among specific disease types, health plan strategies, risk adjusters, or risk-sharing mechanisms within countries.

5. Conclusion

The empirical literature on power of health plan payment models is very limited, presumably because of difficulties in measurement. In this paper, we introduce a new power indicator to evaluate price and volume incentives in health plan payment models. This new power indicator shares similarities with that in GM but is more intuitive and easier to apply in practice. We illustrated this with some empirical applications that can be easily applied to other health plan activities related to subgroups and diseases.

A noteworthy finding from our study is that power varies for price and volume incentives. The reason lies in the fact that many risk-adjusters rely solely based on volume indicators, which do not impact price incentives. In our example, we demonstrate that for diabetes prevention activities, the power for these activities is 0.70 in Medicare Advantage (MA) in the US, which is higher than in the Netherlands, where it is 0.46. An important difference between both countries is that MA has only volume-based risk adjusters and no cost-based risk adjusters. This also explains why the power of price-related activities in diabetes treatment remains 1.00 in MA, but is 0.84—less than one—in the Netherlands.

Power indicators are useful for health plans and policymakers. For example, a power measure helps health plans when implementing new health strategies by conveying information about the extent to which potential cost savings may be offset by the risk-adjusted payment system. In the extreme, very low or even negative power values imply health plans will be very reluctant to implement cost-control strategies for these diseases. For policymakers, power indicators can be useful when designing a risk-adjustment system, as—all else equal—they might prefer risk-adjustment systems with higher power values because cost-control incentives are retained.

Higher power means a health plan gets to keep a higher share of savings from a cost-control strategy. Policymakers might favor certain types of cost-control strategies by health plans and work to ensure a high enough power to motivate plans to implement the strategies. This approach parallels the one used for selection incentives. In the context of selection, policymakers primarily aim to reduce incentives for activities that target vulnerable subgroups and are relatively easy exploited by health plans (Van Kleef et al. 2024). In practice, when designing a risk adjustment system, policymakers should take into account both incentives for certain selection strategies as well as incentives for certain cost control strategies. Our power measure helps a regulator understand the empirical dimensions of the tradeoff.

Additionally, policymakers can use power measures, similar to those computed in section 4, to compare health plan payment models across countries. Such a comparison has not been conducted previously as far as we know. These overall power indicators of volume and price incentives can serve as a baseline for further evaluation of a health plan payment system.

Our research opens many directions for future research. One direction would be to perform power calculations for various cost control strategies and diseases, as we did in section 3. Such calculations would yield more information about which risk adjusters or risk-sharing mechanisms especially tend to diminish cost control incentives. Interestingly, despite the extensive empirical literature on demand-side cost sharing, the effect on power has not been considered. While it is well-known that deductibles and copayments enhance cost control incentives for individuals (Newhouse et al., 1993), the extent to which they dilute cost control incentives of health plans has not been studied.

Another direction for research is to consider the dynamics of incentives. In practice, endogenous risk adjusters often depend on health care usage from previous years. The share of revenue lost later with a reduction in cost now depends on the frequency with which individuals remain in the same plan. Our calculations do not take plan departures into account which may vary by form of service use.

Exploring how health plans respond to lower power values in practice is an important area for research. One notable example is the study of incentives that encourage over- or under-provision of services to deter enrollment by unprofitable members (Geruso et al., 2019). Health plans in the US and elsewhere engage in “upcoding,” a questionable practice intended to increase the risk adjustment score of members and increase plan revenues by providing services that lead to additional diagnostic flags in the risk-adjustment formula (McWilliams, 2025). Services associated with very low power are good candidates for an opportunistic plan to upcode. It would be interesting to test whether the prevalence of upcoding is related to the incentives to do so at the service level.

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Appendix A. Power indicators

In this appendix, we explain the difference between the power indicator developed by Geruso ane McGuire (2016) and our new power indicator as explained in section 2.1.

Using the notation of section 2.1, the power-indicator P_d^{GM} by Geruso and McGuire (2016) can be written as:

$$P_d^{GM} = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left(1 - \frac{R(i) - R_{\sim d}(i)}{C_d(i)}\right)$$

The term in brackets represents the average of individual power measurements. First, GM calculate the power measure for each individual separately, then takes the average across all individuals. The power value in the paper is derived as follows:

$$P_d = 1 - \frac{\sum_{i=1}^{N}\left(R(i) - R_{\sim d}(i)\right)}{\sum_{i=1}^{N} C_d(i)} \; = \; 1 - \frac{R - R_{\sim d}}{C_d}$$

We first calculate the revenues and corresponding costs for the total group of N individuals. Next, we determine the average power by dividing the total revenue difference by total costs. The new power indicator offers advantages over the GM power indicator. First, it is more intuitive, as it reflects the perspective of the entity performing the activity—the health plan. Health plans primarily focus on the overall results, costs, and revenues of enrolled individuals at the plan level, rather than on the power values of individual enrollees. Second, the new power indicator is in some cases easier to apply. While the GM power indicator requires individual-level data, the new power measure relies only on the total sum of revenues and costs associated with the activity or disease. We adopt this latter approach in section 4 to compute overall power values for a health plan payment system. Third, the new power indicator is also more stable. If the denominator in the GM power indicator, $C_d(i)$, approaches zero for a single individual, the resulting value may be infinite. In contrast, using the total sum of costs in the denominator ensures stability, allowing power calculations even when some enrollees experience no cost changes in $C_d(i)$.

Appendix B. Additional information on power calculations of preventing hospitalizations for diabetes patients in the Netherlands and the US

B.1. The Netherlands

For our study, we secured permission to utilize proprietary individual-level data on medical spending. Specifically, we analyzed hospital and total spending for the entire Dutch population covered by basic health insurance from 2017 to 2020 (approximately 16.7 million individuals annually). The data originated from various sources, including health plans, the healthcare institute, the tax collector, and the registration service for social benefits.

Our analysis incorporated risk adjusters applied in the RA-model for somatic care in 2023. There are exogenous risk adjusters, including age, sex, region, source of income, socioeconomic status, institutional status and household size. Endogenous risk adjusters include costs related to durable medical equipment, pharmaceutical costs, prior spending on home care, physiotherapy diagnosis groups, diagnostic cost groups (DCGs), and multiple-year high-cost groups (MHCs). For further details on risk-adjusters in general, see Van Kleef et al. (2018), and Van Kleef and Van Vliet (2022), for specific information about MHCs. Our specific focus was on measuring incentives for preventing hospitalizations among diabetes patients. To achieve this, we emphasized the latter two risk-adjusters: DCGs and MHCs.

Furthermore, we obtained permission to utilize morbidity data from the Nivel Primary Care Database (Nivel, 2022). Nivel routinely collects information from electronic health record systems of general practitioners. This dataset includes details about consultations, morbidity, prescriptions, and diagnostic tests. Diagnoses are coded according to the International Classification of Primary Care, which distinguishes nearly 700 diagnoses and symptoms (Lamberts and Wood, 1987). For each of the 1.4 million registered patients, the dataset indicates whether or not a patient was diagnosed with diabetes in 2019. For additional information about the Nivel Primary Care Database (Nivel PCD), we refer to Vanhommerig et al. (2025).

The methodology we employ comprises the following steps:

1. We begin with the Nivel PCD, which serves as a representative sample of the Dutch population. From this dataset, we select a subset of 87,119 Dutch individuals diagnosed with diabetes in 2019, representing approximately 6.3% of the Nivel PCD population.
2. We connect these diabetes patients to individual-level data that includes hospital and total health care spending. The data covers each individual from 2017 to 2020. Note, we do not observe whether hospital spending is specifically associated with diabetes or other health conditions. Approximately 91% of all diabetes patients incurred positive hospital costs between 2017 and 2020, with around 70% having positive costs in 2020. For the purposes of this analysis, we assume that all hospital costs (inpatient and outpatient costs) for diabetics are solely attributable to diabetes. We define group d as all individuals with diabetes. For group d we compute for each individual hospital costs C_d and average costs $\bar{C}_d$ in 2020.
3. We further link these patients with diabetes to the Dutch RA-system of 2023 applied to the payment year 2020. This linkage enables us to compute individual health plan payments, and their corresponding averages ($\bar{R}$) specifically associated with these patients.Throughout our analysis, we maintain fixed payment weights for the payment year 2020.
4. The Dutch RA-system 2023 operates prospectively. When applied to the payment year 2020 it uses risk adjusters based on individual characteristics from the years 2017 to 2019. Our analyses focuses on two risk adjuster classifications: DCGs, which consist of 26 risk classes plus a separate risk class DCG0 for individuals that are not attributed to any of these 26 groups, and MHCs, which consist of 8 risk classes plus a separate

risk class MHC0 for individuals without multiple-year high costs. To assess the impact on revenue loss associated with DCGs and MHCs, we assume that the prevention program was implemented in 2017 (and subsequent years). The program's effectiveness is reflected in patients' absence from hospitals during the period from 2017 to 2019.

a. Whether an individual's DCG is activated within the RA-system for payment year 2020 depends on hospital use in the preceding year 2019. Since we assume that prevention removes hospital costs in 2019, we assume that all diabetes patients are deactivated in any DCG group in 2020, with each diabetes patient being flagged by risk adjuster DCG0. The loss in revenue for each individual is then computed as the revenue in DCG0 minus the sum of revenues in DCG1-DCG26. We define the total change in revenue as ΔDCG.
b. The activation of a Multiple Year High Costs Group (MHC) is contingent on the *total* health care costs for each individual in the years 2017-2019. To assess the impact associated with MHC, we compute for each diabetes patient total health costs minus hospital costs for the years 2017-2019. Subsequently, we determine whether this decrease in *total* costs results in an individual being moved to a different MHC-category. For each individual, the loss in revenue is determined by the difference in revenues if the individual is shifted to another MHC category. We define the total change in revenue as ΔMHC. We can now compute for each individual $R - R_{\sim d} = \Delta\text{DCG} + \Delta\text{MHC}$, averages $\bar{R}_{\sim \text{d}} = \bar{R} - (\overline{\Delta\text{DCG}} + \overline{\Delta\text{MHC}})$, and average power of volume incentives $P_d = 1 - \frac{\bar{R} - \bar{R}_{\sim \text{d}}}{\bar{C}_d}$.

We apply two calculations. For the first calculation we use hospitalized diabetes patients only. In the main text, we use this example because it is better comparable to the MA example, as it also only involves people with positive hospital costs. In the second calculation we use all diabetes patients, thus also diabetes patients that were not hospitalized. The reason is that a strategy to prevent hospitalizations will be targeted to all diabetes patients. We will show that the difference in power between the two calculations is relatively small.

Figure 1 shows three distributions for hospitalized diabetes patients in 2020. The distribution of hospital costs C_d are below 1000 euros for 44.8% of the diabetes patients. This is related to the fact that many patients have only outpatient hospital costs. The distribution of the differences in revenues, $R - R_{\sim d}$ shows to what extent DCGs and MHCs are responsible for this effect. The average difference in revenue is 1,863 euros, of which 57% is related to DCGs and 43% to MHCs. The distribution of net revenues $(R - R_{\sim d}) - C_d$ is positive for about 35% of the individuals.[11] For these individuals health plan the preventive program is unattractive as the power of incentives is less than zero. On average net revenues are $-2{,}513$ euros indicating that $\bar{R} - \bar{R}_{\sim d} < \bar{C}_d$. Thus the average power of incentives is positive, with an average of 0.46. The first row in Table B1 summarizes the results. In the second row we show the results for all diabetes patients, and find a slightly lower power value of 0.43. Note that total hospital costs C_d do not change in both calculations (although $\bar{C}_d$ will be lower in the second calculation because of a larger population). Only $R - R_{\sim d}$ changes. We can split up this term into hospitalized and non-hospitalized patients in 2020. Since $R - R_{\sim d}$ for hospitalized patients is the same as in the first calculation, we only have to calculate this term for non-hospitalized patients in 2020. This latter term might be positive for diabetes patients with positive hospital costs for the years 2017-2019. For these patients a health plan may receive payments, related to DCGs and MHCs in 2020. These additional payments to health plans for patients that have hospital costs in previous years, but not in 2020, are relatively small and result in a slightly lower power measure of 0.43.

[11] Individual power measures can only be measured for individuals with hospital costs $C_d > 0$.

Whether the prevention program is profitable for health plans depends on the costs of the program and the number of diabetes patients that are affected by the program. Suppose that 5% randomly chosen diabetes patients are affected by the program, then in order for the prevention program to be profitable average costs of the program per individual should be lower than 5%*1,414=71 euros.[12] In a market without risk-adjustment the prevention program would be profitable if average individual costs of the program are lower than 71/0.43=165 euros.

Table B1. *Power of volume incentives for preventing hospitalizations, diabetes patients, the Netherlands, 2020.*

	$\bar{C}_d$	$\bar{R}$	$\bar{R}_{\sim d}$	$\bar{R} - \bar{R}_{\sim d}$	$\boldsymbol{P_d}$	ΔX_l^{volume}	ΔX_m^{costs}
Hospitalized diabetes patients	4,663 €	8,638 €	6,124 €	2,514 €	**0.46**	– 0.33	– 0.21
All diabetes patients	3,227 €	7,235 €	5,371 €	1,863 €	**0.43**	– 0.36	– 0.21

Note: ΔX_l^{volume} refers to the proportion change in power due to DCGs. ΔX_m^{costs} refers to the proportion change in payments due to MHCs. All numbers are rounded and represent averages. € refers to euros.

We next consider incentives for an plan to seek a lower price for hospital treatments for hospitalized diabetes patients. Important is that a price change does not affect use, and that DCG categorization is unaffected. A change in price solely affects health plan's revenues related to MHCs. Table B2 displays the power values for price reductions ranging from 10% to 50%. The reason for the small decline in power is that larger price reductions result not only in larger payment differences $R - R_{\sim d}$, as more individuals move from a higher paid to a lower paid MHC-category, but also in larger costs C_d, as more costs are taken out when prices reductions are larger.

Table B2. *Power of price incentives for different price reductions in diabetes hospitalizations, the Netherlands, 2020.*

Price reduction	10%	20%	30%	40%	50%
Power of price incentives, P_d	**0.84**	**0.83**	**0.82**	**0.82**	**0.81**

Note: All numbers are rounded and represent averages.

[12] If we perform the same calculations for diabetes patients that have only positive hospital costs, i.e., $C_d > 0$, we find similar outcomes. In that case we have average net revenues of 2149 euros (see section 4 in paper). 5% of all diabetes patients corresponds with 70%*5%=3.5% patients with $C_d > 0$. The computations now become 3.5%*2149=75 euros, and 75/0.46=163 euros.

B.2. Medicare Advantage (US)

We analyzed data from 13.5 million individuals represented in the 2020 20% Medicare Research Identifiable File (RIF) sample.[13] We restricted our analysis to a subset of 4.7 million individuals who met the following eligibility criteria in 2020: 1) did not die, 2) had continuous enrollment in Medicare Parts A and B, 3) were aged 65 years or older, 4) did not have end-stage renal disease, and 5) were not dually enrolled in Medicaid.

For these individuals, we extracted ICD-10 diagnosis codes from inpatient[14], outpatient[15,16], and carrier[17,18] claim files. We only included outpatient and carrier diagnosis codes from claims that were associated with at least one eligible CPT/HCPCS code.[19] We mapped diagnosis codes to HCCs using the 2020 Model Version V24 Midyear Final ICD-10 mappings. [20]

A total of 530K eligible individuals (11%) accounted for 780K hospitalizations with an admission date between January 1, 2020 and December 31, 2020. These hospitalizations were associated with 13.1 million ICD-10 diagnosis codes. Among the hospitalizations in 2020, 250K (32%) included a diagnosis that mapped to one of three diabetes-related HCCs (17, 18, 19). For 10K of these hospitalizations (among 9K individuals), the diabetes-related diagnosis was either the admitting or principal diagnosis. Figure 1 shows the distribution of diabetes-

[13] Stanford Center for Population Health Sciences. (2023). Medicare 20% [2019-2020] Enrollment/Summary (Version 1.0) [Base (A/B/C/D)]. Redivis. https://doi.org/10.57761/xg2t-1343
[14] Stanford Center for Population Health Sciences. (2023). Medicare 20% [2019-2020] MedPAR (Version 1.0) [MEDPAR]. Redivis. https://doi.org/10.57761/67t8-9d86
[15] Stanford Center for Population Health Sciences. (2023). Medicare 20% [2019-2020] Outpatient (Version 1.0) [Base Claim]. Redivis. https://doi.org/10.57761/9ct0-kf53
[16] Stanford Center for Population Health Sciences. (2023). Medicare 20% [2019-2020] Outpatient (Version 1.0) [Revenue Center]. Redivis. https://doi.org/10.57761/9ct0-kf53
[17] Stanford Center for Population Health Sciences. (2023). Medicare 20% [2019-2020] Carrier (Version 1.0) [Line]. Redivis. https://doi.org/10.57761/w5a5-yb97
[18] Stanford Center for Population Health Sciences. (2023). Medicare 20% [2019-2020] Carrier (Version 1.0) [Base Claim]. Redivis. https://doi.org/10.57761/w5a5-yb97
[19] https://www.cms.gov/files/zip/2020-medicare-risk-adjustment-eligible-cpthcpcs-codes.zip
[20] https://www.cms.gov/medicare/health-plans/medicareadvtgspecratestats/downloads/2020midyearfinalicd-10-cmmappings.zip

related hospitalization costs. The average Medicare payment $\bar{C}_d$ for diabetes-related hospitalizations was \$13,500.[21]

We computed individual risk scores based on the coefficients in the 2020 V24 Model Software for the community-dwelling, non-dual, aged population.[22] For example, the average risk-score for individuals with a hospitalization where the principal diagnosis is diabetes is 3.3. For this computation we used a 20% sample and selected inpatient claims (admitting or principal diagnosis) for ICD-10 diagnosis codes mapped to a diabetes-related HCC. We also computed counterfactual risk scores dropping diagnosis codes from individuals' first diabetes-related hospitalization where the diabetes-related diagnosis was either the admitting or principal diagnosis. We computed the revenue difference, $R - R_{\sim d}$, as the difference between observed and counterfactual risk scores, multiplied by the CMS denominator used to calculate relative coefficients for the V24 risk score (see Figure 1) The average over all patients $\bar{R} - \bar{R}_{\sim d}$ equals \$4,100. Next, we computed net revenue, $(R - R_{\sim d}) - C_d$, by subtracting diabetes-related hospitalization costs from the revenue difference (see Figure 1) For 11% of all individuals, net revenue was positive. For these individuals, power was less than zero.

Table B3. Average power of volume incentives for preventing hospitalizations, diabetes patients, United States Medicare Beneficiaries, 2020.

	$\bar{C}_d$	$\bar{R}$	$\bar{R}_{\sim d}$	$\bar{R} - \bar{R}_{\sim d}$	$\boldsymbol{P_d}$	ΔX_l^{volume}	ΔX_m^{costs}
Hospitalizations with diabetes as the admitting or principal diagnosis	13,500 \$	31,200 \$	27,100 \$	4,100 \$	**0.70**	– 0.30	-
Hospitalizations with diabetes as any contributing diagnosis	14,900 \$	24,700 \$	20,000 \$	4,680 \$	**0.68**	– 0.32	-

Note: ΔX_l^{volume} refers to the proportion change in power due to HCCs. All numbers are are averages and rounded off. \$ refers to US-dollars.

[21] Includes the inpatient Medicare payment, claim pass-through per diem payments, and carrier payments between the admission and discharge dates.
[22] https://www.cms.gov/files/zip/2020-model-software.zip

Finally, we calculated power, using equation (2): $P_d = 1 - \left(\frac{\bar{R}-\bar{R}_{\sim d}}{\bar{C}_d}\right) = 0.70$. The results are summarized in the top row of Table B3.

As a sensitivity analysis, we computed power for all diabetes patients for the first hospitalization where diabetes was included as any contributing diagnosis (i.e., not limited to just admitting or principal diagnosis). The results can be found in the bottom row in Table B3. We find similar results, with power of 0.68.

All analyses were conducted using R version 4.0.3 (R Project for Statistical Computing).

Appendix C. Additional information on power calculations of the six countries

In this appendix, we provide information on the power calculations in section 4 of the paper. In the following sections, we will discuss each country separately. Note that there is also a separate Excel file titled "Country power calculations" with more information about the calculations for each country.

C.1. Australia

The outline of the private health insurance system and the risk adjustment system of Australia can be found in Paolucci et al. (2018) and Henriquez et al. (2023). For our power calculation all information was updated for 2021. This information and calculations can be found in a separate excel sheet "Australia" in the excel file "Country power calculations". The Australian relies solely on risk-sharing features. Australia employs a high-risk pool in which 82% of individual claims exceeding the threshold of $50,000 AUD (discounted using an age-based pool) are reimbursed by the regulator. Risk sharing amounts to approximately 45% of total healthcare spending, resulting in a reduction of power incentives to 55%.

C.2. Germany

The German risk-adjustment system for the public health insurance system, operated by sickness funds, consists of exogenous and endogenous risk adjusters, as well as risk sharing. For 2021, the mean health care expenditure included in the German risk adjustment mechanism is 3,219 €. This figure does not include the admin costs and the expenditure for supplementary benefits (less than 1% of total spending of sickness fund insurance) as well as the costs for disease management programs. Sick leave payment is neither included in this figure. So, this is the mean of individual expenditure. The *exogenous* risk adjusters of the German risk adjustment formula include 40 age-sex classes and 80 regional classes derived from 8 different regional variables (which may differ in different years). The system includes 495 Hierarchical Morbidity Groups (HMG) which form the *endogenous* risk adjusters in this system. The morbidity classification model is based on the HCC (hierarchical condition categories) developed by Ash et al. (2000). The model was adapted to the German system, by splitting morbidity groups according to age, sex, or prescription of drugs. HMGs are volume or use-based risk adjusters as they are assigned to individuals according to diagnoses from inpatient stays and outpatient visits. The risk-adjusted payment of HMGs account for about 54% of the total budget. Additionally, there is *risk-sharing* in form of a high-cost pool reimbursing 80% of all annual individual expenditure exceeding 100.000 € (a threshold, which is adapted every year). Risk sharing of the regulator accounts for about 3% of the total budget. For more information, we refer to Wasem et al. (2018) and Bundesamt fur Soziale Versicherung (2023) for a very detailed description of the public insurance system and risk equalization system. A shorts summary of the calculations can be found in the sheet “Germany” in the excel file “Country power calculations”.

C.3. Israel

The outline of the health plan payment system of Israel can be found in Brammli-Greenberg et al. (2018). For our power calculation all information was updated for 2021. This information and calculations with data sources can be found in a separate sheet “Israel” in the excel file “Country power calculations”. Israel has a single volume-based risk category that relies on diagnoses, distinguishing five disease classes: thalassemia major, Gaucher’s disease, kidney dysfunction, haemophilia and AIDS. These five disease classes accounted in 2021 for a spending share of 4% within the payment system. Demand-side cost-sharing accounts for about

6% of the budget. Moreover, there are retrospective payments by the regulator that acoount for about 10% of the budget.

C.4. the Netherlands

For the country comparison we used the Dutch risk-adjustment system of 2021. This is likely the only system that differentiates between volume and cost-based risk categories within their risk-adjusted capitation model. We summarize here the main results and refer for more detailed calculations to the sheet "the Netherlands" in the excel file "Country power calculations". It comprises five exogenous risk adjusters based on age and sex (42 classes), region (10 classes), socioeconomic status (12 classes), employment status (42 classes), and individuals in long-term care (12 classes). The latter twelve risk classes, related to the long-term care services, are not classified as an endogenous risk adjuster because long term care services fall outside the Dutch basic benefit package. The system includes four endogenous volume-based risk categories: diagnostic cost groups (DCG, 26 classes), pharmaceutical cost groups (PCG, 38 classes), physiotherapy diagnostic cost groups (FDG, 4 classes) and durable medical equipment (HCG, 14 classes). Examples of durable medical equipment are CPAP devices, devices for stoma, or leg protheses. In terms of the payment system, these volume-based categories collectively represent a spending share of about 28%. The system comprises two endogenous cost-based risk categories, both of which incorporate dummy variables for individuals with high spending in multiple prior years: one for somatic care (MHC, 8 classes) and another for home care and geriatric rehabilitation care (MVV, 9 classes). Some examples of MVV-classes are "individual is three times in last three prior years in top 15% cost-group" and"individual has sum of costs in caring and nursing over 3 years in top 2 percent". These two cost-based categories collectively represent a spending share of about 28%. Finally, the Dutch has a mandatory and voluntary deductible which represent a spending share of about 7%. We summarized the funding sources in Table C1. Note that we excluded temporary risk-sharing mechanisms in 2021 from this analysis due to COVID-19. As a result, the average power of volume incentives is $1-28\%-28\%-7\%=0.37$ and power of price incentives is $1-28\%-7\%=0.65$.

Table C1. Funding sources for the Dutch health insurance system, 2021.

Total public healthcare expenditures (million euros)	**49,500**
Plan Payments (total, million euros)	
Miscellaneous payments (Exogenous risk category)	19,038 (39%)
PCGs, DCGs, HCGs and FDGs (Volume-based risk adjusters)	13,363 (27%)
MHCs, MVVs (Cost based risk adjusters)	13,741 (28%)
Public contributions (Risk-sharing mechanism)	- (0%)
Copayments (Risk-sharing mechanism)	3,359 (7%)

C.5. Switzerland

The Swiss payment system for the compulsory health insurance system, is detailed in Schmid et al. (2018). The funding sources for plan payments in 2021 are summarized in Table C2.

The Swiss system contains two endogenous volume-based risk adjusters. The first risk adjuster is related to total transfers when staying in a hospital or nursing home and comprises of 1560 risk classes, with each class defined by a combination of age, sex, canton, and whether there was a hospital or nursing home stay over at least three consecutive nights in the previous year. The monetary transfers within the payment system, pertaining to this risk category, account for a total spending share of about 12%. The second risk adjuster consists of transfers related to PCG and relates to 34 pharmaceutical cost groups, representing a total spending share of 20%. In total, the two volume-based costs risk-adjusters account for a total spending share of 32%. The Swiss system contains two risk-sharing mechanisms. First, there is a risk sharing mechanism by the cantons. The Swiss cantons pay retrospectively on average about 55% of all inpatient costs within a canton. Moreover, there are substantial copayments by consumers in Switzerland that account for about 11% of the costs. We consider the remaining payments as exogenous. A part of these payments concerns expenditures related to children under 18, as the first risk category related to a hospital or nursing home holds only for individuals of 19 years and older. The calculations of Switzerland can be found in the sheet "Switzerland" in the excel file: "Country power calculations".

Table C2. Funding sources for the Swiss compulsory health insurance system, 2021 (in million Swiss Francs).

Total public healthcare expenditures	**43,577**
Plan Payments (total)	
Miscellaneous payments (Exogenous risk category)	14,786 (34%)
Total transfers when staying in hospital or nursing home (Endogenous (volume) risk category)	5,818 (13%)
Total transfers related to PCG (Endogenous (volume) risk category)	9,575 (22%)
Public contributions (Risk-sharing mechanism)	8,605 (20%)
Copayments (Risk-sharing mechanism)	4,794 (11%)

C.6. Medicare Advantage (US)

The payment system in US MA, as detailed in McGuire and Newhouse (2018), incorporates exogenous risk adjusters, including age, sex, and an indicator for original eligibility due to disability. In 2020 it had one volume-based risk-category with eighty-six hierarchical condition categories (HCCs). The risk adjustment data for MA are not publicly available, and therefore we used data of individuals from Traditional Medicare. The numbers in Table 2 are based on a dataset of 4.7 million eligible individuals represented in the 20% Medicare RIF sample in 2020, which is the same dataset explained and used in Section 3 and Appendix B.2. Note that MA has only volume-based risk adjusters; it does not have cost-based risk adjusters, and there is no risk sharing by a regulator or demand-side cost sharing.