Volume LXII No. 1
June 2025

p-ISSN 1655-1516
e-ISSN 2984-8156

The Philippine Review of Economics

ARTICLES IN THIS ISSUE

A joint publication of the
University of the Philippines
School of Economics
and the **Philippine Economic Society**

PRE
The Philippine Review of Economics
A joint publication of the UP School of Economics (UPSE)
and the Philippine Economic Society (PES)

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Publication Information: The PRE (p-ISSN 1655-1516; e-ISSN 2984-8156) is a peer-reviewed journal published every June and December of each year. A searchable database of published articles and their abstracts is available at the PRE website (http://pre.econ.upd.edu.ph).

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Acknowledgments: The PRE gratefully acknowledges the financial support towards its publication provided by the Philippine Center for Economic Development (PCED). The *Review* nonetheless follows an independent editorial policy. The articles published reflect solely the editorial judgement of the editors and the views of their respective authors.

The Philippine Review of Economics

Vol. LXII No. 1
June 2025
p-ISSN 1655-1516
e-ISSN 2984-8156
DOI: 10.37907/ERP5202J

PRE The Philippine Review of Economics
62(1):1-26. DOI:10.37907/1ERP5202J

Consumer profiling, price discrimination, and consumer privacy

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This paper considers a monopolist who exercises first-degree price discrimination by acquiring consumer data to infer reservation prices. The monopolist uses profiling technology to obtain consumer information whose cost is a function of the fraction of consumers it profiles. We first describe the market equilibrium where consumers do not have access to privacy technology that prevents the monopolist from acquiring their data. The paper then introduces a costly privacy technology that allows consumers to prevent their information from being obtained and used by the monopolist. Equilibrium analysis shows two important results that depend on the level of privacy costs. With sufficiently cheap privacy technology, we show that the monopolist profiles fewer consumers compared to when privacy is not an option for consumers. This reduces the incidence of price discrimination in the market. However, if privacy cost is sufficiently expensive, the monopolist profiles the same fraction of consumers as in the case when privacy was not an option. In this case, privacy technology does not reduce the incidence of price discrimination. Regardless of the level of privacy cost, however, the availability of privacy technology to consumers induces the monopolist to set a higher uniform price level for consumers it was not able to profile. Also, regardless of the cost of privacy, this combination of strategies on profiling and uniform price level reduces the incentive of consumers to use the privacy technology and results in an equilibrium where no consumers choose to privatize. Thus, in equilibrium, privacy technology only acts as a deterrent, and can only function as such, against aggressive consumer profiling and price discrimination if its cost is sufficiently low.

JEL classification: L12, D42, D82
Keywords: price discrimination, monopoly, consumer privacy

1. Introduction

1.1. Consumer profiling

The current state of information technology allows firms to extract a wide variety of data ranging from images, texts, and socio-economic information, among others, from consumers and other agents in large volumes and

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high velocity. These data, which are generally referred to as Big Data, are information assets characterized by high volume, velocity, and variety that require specific technology and analytical methods for use [Mauro et al. 2016; Fotaki et al. 2014]. One of the important drivers of interest in big data analytics is its potential to allow firms to optimize their marketing, pricing, and other business decisions [Hofacker et al. 2016]. Together with the availability of big data, the rise of interconnected personal devices creates a situation where the more information consumers provide, the more firms and enterprises can tailor their business strategy to the consumers' desires [Barutcu 2017]. The key role of big data analytics here is to profile consumers and give a more in-depth understanding of customers' behavior and preferences which is something that traditional market knowledge might fail to offer. To accomplish this, many firms resort to gathering important information from consumers through the use of sophisticated data extraction technologies and analytic techniques.

Consumer profiling is especially true for transactions occurring on online platforms such as Amazon, Netflix, and Facebook.[1] These sites routinely gather data from their online customers and use them for various purposes. Casual observation on streaming websites like YouTube, for example, shows how big data analytics and corresponding algorithms play a role in what contents and advertisements an individual sees based on their previous interaction with the platform. Facebook *likes* (and more generally *reactions*) on the other hand can be used to predict a person's highly sensitive attributes such as sexual orientation, ethnicity, religious and political views, among others. with some degree of accuracy [Kosinki et al. 2013]. Naturally, political issues such as privacy and security emerge with consumer profiling. For example, insights gained from these data can be used to design targeted political campaigns to sway people for or against certain political agendas.[2] Generally, countries differ in how they deal with these issues. In the Philippines for example, there is no specific law that directly addresses privacy issues on social media/online platforms [Brutas n.d.]. However, the most relevant statute to this is the Data Privacy Act of 2012 (RA 10173). The act provides for what is lawful processing of personal information that applies to both public and private institutions. The law requires, among other things, that personal information processing is done with the consent of the person whose information is being processed. The personal information holder (i.e. the institution that gathered personal information) is also allowed to pursue the processing of data if it is predicated on a legitimate interest of their institution.

[1] Based on the respective privacy policies of these firms.

[2] The 2016 US Presidential election provided a picture of how data analytics from information in social media can have tremendous social repercussions. Although 'voluntarily' provided by consumers, the information provided to and analyzed by Cambridge Analytica was allegedly used to sway voters 'at the margin' in favor of the now President Donald Trump. This was done by sending voters targeted political campaign ads based on the personal information gathered from them.

Aside from these political challenges posed by big data, important economic issues can also come to the fore. Theoretically, this information can potentially give firms the ability to personalize product advertisements sent to profiled consumers. Another potential use of personal information gathered through consumers' online activities is price discrimination, which is the central interest of this study. This paper explores a monopoly market to analyze the potential consequences of the use of data to exercise first-degree price discrimination and the consequent privacy decisions of consumers.

To provide a brief overview, this paper analyzes a monopoly market where a single firm has access to a costly tracking technology that allows it to know the reservation prices of some of its consumers. This allows the monopolist to practice first-degree price discrimination against the profiled consumer. The firm chooses the fraction of consumers profiled in the market. This *endogenizes* the profiling *reach* of the monopolist. In this market, I analyze two alternative environments: (1) a case where consumers cannot privatize and hide their reservation price and (2) a case where the consumers have access to a costly privacy technology that allows them to hide their reservation price from the monopolist. It follows that the fraction of consumers who will hide is endogenous in the second environment. What we find, however, is that in both environments, no consumer uses the privacy technology. The reason why no consumer uses the privacy technology in the first case is obvious; it is not available. In the second case, the monopolist will find it optimal to set a sufficiently high uniform price level and sufficiently low level of tracking reach such that consumers have no incentive to use the privacy technology. This results in a lower tracking reach, and hence a lower incidence of price discrimination, but a higher uniform price level in the market. The privacy technology then serves as a deterrent to price discrimination.

1.2. Price discrimination and consumer profiling

Price discrimination exists when there is a variation in the price of the same commodity that cannot be explained by variation in marginal costs [Stigler 1987]. Following the terminology of Pigou [1920], we can classify price discrimination into three categories. First is the first-degree or perfect price discrimination. First-degree price discrimination exists when firms charge each consumer their valuation for the commodity it sells such that the firm captures all the consumer surplus. Second-degree price discrimination, on the other hand, involves charging consumers based on the quantity bought (ex. bundle pricing and quantity discounts). This type of price discrimination is also known as non-linear pricing, as the total payment of buyers does not linearly depend on the quantity of the commodity purchased. When prices vary across different market segments, on the other hand, we say that third-degree price discrimination exists. Classic examples of third-degree price discrimination are student and senior citizen discounts. Both second and third-degree price discrimination involve sorting consumers into broad groups. However, second-degree price discrimination sorts individuals via pricing schedules, which leads consumers to self-select via non-linear pricing [Stole 2007].[3] This is in contrast with third-degree price discrimination which requires the firm to sort consumers into segments via some exogenous criterion such as location, gender, etc., after which all consumers belonging to a single segment pay the same price. Alternatively, it can be argued that second-degree price discrimination results in consumers sorting themselves.

Normally, price discrimination allows firms to extract consumer surplus and increase their profits. However, the practice of price discrimination can only exist under three important market conditions. First, firms must possess some degree of market power that allows them to charge a price above marginal cost. This condition entails some degree of price-setting power. Thus, it is easier to expect price discrimination to persist in monopoly and oligopolistic environments where firms have substantial market power. Secondly, firms must be able to sort consumers based on some observable characteristics, especially in the case of first and third-degree discrimination, or by some other sorting mechanism in the case of second-degree price discrimination. Lastly, arbitrage across different-priced goods must be infeasible. It can be shown that with arbitrage between consumers with different valuations of goods, price discriminatory behavior cannot be an equilibrium outcome. Arbitrage is conditional on the degree of transferability of both commodity and utility among consumers. The lower the degree of transferability and/or utility of the commodity, the more difficult for arbitrage to exist. Product differentiation and large transaction costs of resale are, therefore, effective hurdles to arbitrage and can make price discrimination more feasible [Branco and Brossard-Ruffey 2017].

Unlike second and third-degree price discrimination, most of the interest in first-degree price discrimination is only driven by academic curiosity. Especially in the time of Pigou, first-degree price discrimination was seen as "scarcely ever practicable" since it requires information on consumer valuation which is very hard, if not impossible, to observe. However, the current wealth in consumer information in the form of big data and the emergence of more advanced data analytics technologies puts the supposed impracticability of first-degree price discrimination into question. Firms now can access vast amounts of consumer information that can be used to estimate consumer valuations, which in turn, can be used to practice first-degree price discrimination provided that the other market conditions are also satisfied.

There was already a wealth of literature that explored price discrimination even before the use of big data analytics. The models in this literature range from monopoly market settings to models where competitive forces among firms exist. Stole [2007] provides a useful review of some of these models especially those

[3] Pigou did not consider second degree price discrimination as a mode of self-selection. See Stole [2007] for discussion.

in competitive environments.[4] However, models of price discrimination that are closest to the present study are those that make explicit the source and nature of the requisite consumer information for first-degree price discrimination to exist. Incorporation of the characteristics of consumer information allows us to analyze more thoroughly the effects of price discrimination in the context of data analytics. The models allow insights into the effects of factors like data gathering and consumer profiling cost, data provision and estimation accuracy issues, as well as consumer responses like the use of online privacy services, among others, that might otherwise be absent in models where the enabling source of price discrimination is implicit. For example, Chen and Ayer [2002] explored a model where firms' profiling cost is an increasing function of the level of its 'reach'. Belleflamme and Vergote [2016], Belleflamme et al. [2017], and Esteves [2014], on the other hand, explored accuracy issues relating to consumer valuation estimation. The paper by Acquisti and Varian [2005], Montes et al. [2018], as well as the same paper by Belleflamme and Vergote [2016] provide a theoretical analysis of how consumer privacy affects market equilibrium in monopoly and duopoly markets.

Most models of price discrimination share several key characteristics. First, most models are in game-theoretic setup. As with most economic models, the game-theoretic setup allows an analyst to fully understand interactions between and among economic agents. It is an approach to analyze how a system finds its equilibrium (or evolves) taking into consideration the motivations and strategies available to agents in the game. Second, the models operate as a pricing strategy game, which naturally, if it exists, yields an equilibrium in prices before quantity can be computed. The pricing game is seen as a more natural environment for models with price discrimination [Stole 2007]. Third, the models make explicit consumer heterogeneity, especially with respect to their valuations of goods. This heterogeneity of consumers is at the core of models with price discrimination and consumer profiling. This is because consumer profiling and the associated price discrimination are more easily described by allowing consumer valuation of a good to vary among one another. The use of a location in a Hotelling line as a proxy for preference and consumer distribution over reservation prices are two of the most common methods encountered in literature to model consumer heterogeneity. The models in this paper will generally follow these broad characteristics of price discrimination models.

The present paper aims to analyze how a monopolist with the capacity to price discriminate will decide on the extent of its consumer profiling, especially in the case where consumers can opt to privatize their personal information with a cost. Crucial to this analysis is the assumption that consumer profiling allows the

[4] Nevertheless, and for reasons stated above, much of the literature are on second degree and third degree price discrimination. See for example, Fudenberg and Villaboas [2005] for third-degree price discrimination or Stokey [1979] for her seminal work on intertemporal, third-degree price discrimination.

firm to know a consumer's valuation of the good, which then allows it to offer price-discriminatory price. We show that under some conditions, the capacity of consumers to privatize their information acts as *a deterrent to profiling* by the price-discriminating monopolist. That is, the threat of privatizing keeps the firm from pursuing more aggressive consumer profiling. This leads to firms choosing to track a smaller fraction of consumers, which in turn lowers the number of consumers offered discriminatory price levels. Absent this consumer option to privatize, we show that the monopolist profiles more consumers. We also show that the presence of privacy technology induces the firm to *set a higher uniform price level* for those consumers it was not able to track.

In the next section, we will briefly introduce a standard monopoly model without consumer profiling and price discrimination. Against this benchmark, the third section will compare the market outcomes when there is price discrimination. The fourth section will provide an analysis of the case when consumer privacy technology is available.

2. Benchmark standard monopoly model

Throughout this paper, we will assume a market with a unit mass of consumers uniformly distributed over the unit line with respect to their valuation of the goods being sold by the monopolist. We denote the valuation of consumer i as r_i. The valuation ranges from [0,1]. Thus, the probability density function (PDF) is given by $f(r) = 1$ with the support [0,1]. For simplicity, we are also assuming that the monopolist's cost of production is zero.

The consumer has a unit demand for the good. For any price p, the demand of any consumer i with valuation r_i is given by

$$D_i(p) = \begin{cases} 1 \text{ if } r_i - p \geq 0 \\ 0 \text{ if } r_i - p < 0 \end{cases} \tag{1}$$

From these assumptions, it follows that the market demand is given by the equation

$$D(p) = 1 - p \tag{2}$$

where p is the uniform price charged by the monopolist for its good. The profit function of the monopolist, π, is given by the equation

$$\pi(p) = p(1 - p) \tag{3}$$

The problem of the monopolist is to maximize (3) by choosing the optimal uniform price p_o to be charged. With zero marginal cost, the profit-maximizing price level is equal to $p_o = 1/2$. The maximum profit is equal to $\pi_o = 1/4$. The consumer surplus in equilibrium is $CS_o = 1/8$. Defining total welfare in this market as $W_o = CS_o + \pi_o$, we get $W_o = 3/8$ in equilibrium. Throughout this paper, we will refer to these price, profit, consumer surplus, and total welfare as *benchmark* levels as they result from a monopoly market without price discrimination.

3. Price discrimination, endogenous consumer profiling, and consumer privacy

3.1. The reach and cost of consumer profiling

In this section, we introduce the model which incorporates a profiling technology that allows the monopolist to know the reservation prices of consumers. We are concerned with first-degree price discrimination as defined by Pigou [1920] and as used in the models of Chen and Ayer [2002] Belleflamme & Vergote [2016], Belleflamme et al. [2017], and Bar-Gill [2018]. The model is closest to that of Belleflamme & Vergote [2016] but differs in two important ways. In our model, (1) consumer profiling is costly and (2) the fraction of consumers to be profiled is chosen by the firm and is, therefore, endogenous to the model. These are in contrast to the original model of Belleflamme & Vergote [2016] where the cost of technology is zero and the fraction of profiled consumers is exogenously determined. Here, we will incorporate a costly technology whose cost depends on its *reach*—how large the fraction of consumers the monopolist firm can profile. The profiling technology has a level of reach denoted by $\lambda \in [0,1]$. This parameter measures the fraction of consumers whose reservation price is (correctly) estimated by the firm. In this segment, the firm will charge the corresponding reservation price of each consumer. Note that in the discussion of Belleflamme & Vergote [2016], λ is referred to as the accuracy or precision of profiling technology. In this study, λ is best thought of as the 'reach' of the technology to reflect that (1) what the firm chooses is the fraction of consumers that will be profiled and *not* the probability that its estimate of the consumer's reservation price is correct, and (2) that once the consumer is profiled (i.e., within the reach of the monopolist's profiling) the estimate of her reservation price by the firm must be accurate, which is similar to how Chen & Ayer [2002], Montes et al. [2018] and Belleflamme et al. [2017] modeled consumer profiling. Once a consumer is profiled, she is offered the good at her reservation price r_i. If the consumer is not profiled, the good is offered to her at the uniform price level. It follows that the fraction $(1-\lambda)$ is the fraction of consumers whose reservation price is not known and, therefore, must be charged a uniform price. This essentially divides the market into two groups: the profiled with size λ and unprofiled consumers with size $(1-\lambda)$.

We also assume that the probability that an individual is profiled given the level of reach chosen by the monopolist is independent of her valuation. This implies that given any level of reach, high-valuation consumers are not more likely to be profiled than low-valuation consumers and vice versa.

Another firm exists which provides the profiling technology to the monopolist. We are assuming that this technology firm is not behaving strategically. The case of strategically behaving technology firms is explored by Montes et al. [2018]. It is also assumed in this paper that arbitrage involves prohibitively high transaction costs. This prevents a consumer from reselling the commodity at a higher price to another consumer, thus allowing price discrimination to emerge in equilibrium.

The cost of technology, T, is a function of the level of reach λ with the following properties: (1) the cost is increasing at an increasing rate in the level of reach λ, (2) the limit of T as λ approaches the maximum attainable reach, one, is infinity. These properties reflect the view that consumer profiling becomes more and more expensive as the firm tries to reach a higher fraction of the consumer population. Similar to Grossman & Shapiro [1984], this may be due to media platform saturation or heterogeneity in preferences to use platforms where data extraction may take place. Thus, the firm must incur an increasing cost as it attempts to increase the reach of the technology. The cost function T is specified as

$$T = \frac{\tau \lambda}{1 - \lambda} \tag{4}$$

where τ is the cost parameter and λ is the level of reach chosen by the firm. The firm, therefore, can choose any level of technology within the range [0, 1]. This approach in modeling the cost of profiling is similar to Chen & Ayer [2002] in so far as the cost is a function of the level of reach of profiling. However, it differs from Chen and Ayer [2002] because, in the latter, the cost of profiling as the reach approaches one is finite.[5]

We maintain the following assumptions: (1) the cost of producing the good sold by the monopolist is zero, (2) we have a unit mass of consumers uniformly distributed in their valuation ranging from [0,1] and (3) for each level of price p, each consumer i with valuation r_i has a unit demand described by Equation (1) under the standard setup without profiling and price discrimination. The total demand, $D(p)$ for the monopolist's good is, therefore, given by the survival function, which is Equation (2).

3.2. Monopoly equilibrium with price discrimination

The problem of the monopolist is to choose p^* and λ^* that maximize the profit generated from two sources: the profiled segment (price discrimination) and the unprofiled (uniform price) segment of the market.[6] To derive the equation for profit from these two sources, we first ask the following questions: What is the expected revenue from consumers the firm was able to profile as well as the consumers it was not able to profile? We use the term expected because before deciding whether to use and to what extent (level of λ) the profiling is to be used, the firm is *not* yet

[5] In Chen and Ayer [2002], firm i's cost of profiling is given by the function $c_i(a_i) = (ka_i^2/2)$ where a_i is the level of reach of firm i.

[6] We use * to denote equilibrium values in this market with price discrimination

certain which λ fraction of the population is going to be part of the profiled segment (and consequently consumers not part of the profiled segment).

For a given distribution function $F(r)$ of valuation r with mean μ_r with N consumers, we show in Appendix A.1 that the expected revenue from the profiled segment which we denote as R_t given any level of reach λ is

$$E(R_t|\lambda) = \lambda\mu r \tag{5}$$

while the the expected revenue from the unprofiled segment denoted as R_o is given by

$$E(R_o|\lambda) = Np(1 - \lambda)(1 - F(p)) \tag{6}$$

where p is the uniform price to be charged to consumers not profiled by the monopolist.

This implies that if the firm wants to price discriminate, it must set λ and p without any prior knowledge about who are the consumers who will be exactly profiled. In effect, the firm must decide whether to use the profiling technology based on the expected revenue from the two segments.

As mentioned earlier, the expected revenue of the firm is the sum of revenues from both the profiled and unprofiled segments. Since we have a unit mass of consumers distributed uniformly over [0,1] and denoting π_t as the expected profit, we get the uniform distribution case of the same expression in the model of Belleflamme and Vergote [2016],

$$\pi_t = [(\lambda/2) + (1 - \lambda)\, p\, (1 - p)] - \frac{\tau\lambda}{1 - \lambda}\ . \tag{7}$$

Differentiating with respect to p and λ gives us the following first-order optimality conditions.

$$\frac{\partial \pi_t}{\partial p} = (1 - \lambda)\, (1 - 2p) = 0 \tag{8}$$

$$\frac{\partial \pi_t}{\partial \lambda} = \frac{1}{2} - p(1 - p) - \frac{\tau}{(1 - \lambda)^2} = 0 \tag{9}$$

Notice that since λ must be positive, the level of price p^* the solves Equation (9) is the same as the benchmark case. That is, $p^* = p_o$. It follows that the level of profiling that maximizes profit must be

$$\lambda^* = 1 - 2\sqrt{\tau} \tag{10}$$

At (p^*, λ^*), the following are true: (i) $\partial^2\pi_t / \partial p^2 < 0$, (ii) the cross derivatives $\pi_{tp\lambda} = \pi_{t\lambda p} = 0$, and (iii) $\partial^2\pi_t / \partial\lambda^2 < 0$.

These three preceding expressions imply that the determinant of the Hessian, $\mathbf{D}(\pi_t)$, evaluated at (p^*, λ^*) is positive,

$$D(p^*, \lambda^*) = \frac{\partial^2 \pi_t}{\partial p^2}\frac{\partial^2 \pi_t}{\partial \lambda^2} - (\pi_{p_o \lambda})^2 > 0 \tag{11}$$

which, with $\pi_{tp_o p_o} < 0$ and/or $\pi_{t\lambda\lambda} < 0$ indicates that (p^*, λ^*) is a maximizer of π_t.

Suppose high-valuation consumers are more likely to be tracked, then we could expect the uniform price level $p^* < p_o$. The lower p^* maximizes the profit of the firm over the low-valuation consumers who are less likely to be tracked. However, the solution shows that the monopolist will not find it optimal to deviate from the uniform price level p_o such that even with price discrimination and profiling, it still charges p_o to unprofiled consumers. This is due to the independence of consumers' valuation from their probability of being tracked and offered a discriminatory price. Since all consumers have an equal probability of being tracked being λ, the monopolist will find it optimal on average to keep its uniform price level at p_o.

The result for λ^* in Equation (10) is more straightforward to interpret. As the cost parameter τ increases, the level of profiling λ^* decreases in equilibrium. Notice that when profiling is costless such that $\tau = 0$, we expect the monopolist to fully track the market with $\lambda^* = 1$. However, the monopolist will find it optimal not to track any consumers if the cost parameter $\tau \geq 1/4$. This indicates that equilibrium with price discrimination can only emerge if the cost parameter is sufficiently low such that $\tau \in [0, 1/4]$, otherwise, the market reverts to the benchmark case. We formalize this result in the proposition below.

Proposition 1. *If the cost parameter is sufficiently low such that* $\tau \in [0, 1/4]$ *then the monopolist will track a positive fraction of consumers and there will be price discrimination in equilibrium, that is* $\lambda^* \in [0,1]$.

The profit of the monopolist in equilibrium is given by

$$\pi_t^* = 1/2 + \tau - \sqrt{\tau} \tag{12}$$

where $\tau \in [0, 1/4]$. As expected, the profit gained from price discriminating is higher than the benchmark if the cost parameter is sufficiently low as indicated in Proposition 1. The profit gains due to price discrimination can be expressed as

$$\Delta\pi = \pi_t^* - \pi_o \tag{13}$$

From this, we can state the following proposition.

Proposition 2. *If* $\tau \in [0, 1/4]$, *then (a) profit as a price discriminating monopolist is higher than as a benchmark monopolist and (b) the gains from price discrimination vanish as* τ *approaches* 1/4 .

Part (a) of the Proposition 2 directly follows from Proposition 1 while part (b) can be verified by noting that $(d\Delta\pi/d\tau) = 1 - 1/2\sqrt{\tau}$ and is negative over the range $\tau \in (0, 1/4)$. This indicates that as profiling becomes more costly, the gains from price-discriminating decreases. Further, due to the character of the cost function $T(\lambda)$, the gains from price discrimination vanish faster as profiling becomes more and more costly.

3.3. Welfare analysis

The consumer surplus is enjoyed by consumers whose reservation price is above $\sqrt{p_o}$ but is not profiled by the monopolist. The size of this segment is 2τ. The consumer surplus can be expressed as

$$CS_t = \frac{\sqrt{\tau}}{4} \tag{14}$$

which unambiguously increases with the cost of technology τ. It is also important to note that Equation (14) can be expressed as

$$CS_t = 2\sqrt{\tau} CS_o \tag{15}$$

It is easy to see that if $\tau \in [0, 1/4]$ then $CS_t < CS_o$ and consumers are worse off since the monopolist tracks, price discriminates, and extracts consumer surplus equivalent to λ^* of the benchmark surplus CS_o. The impact of changes in τ is also important to note: the consumer surplus decreases as profiling becomes cheaper since the monopolist will be able to track a higher fraction of consumers in the market and offer discriminatory price levels. We state these results in the following proposition.

Proposition 3. *If* $\tau \in [0, 1/4]$ *then (a) consumers are worse off with surplus extraction equivalent to* $\lambda^*/8$ *and (b) consumer surplus decreases as profiling becomes cheaper.*

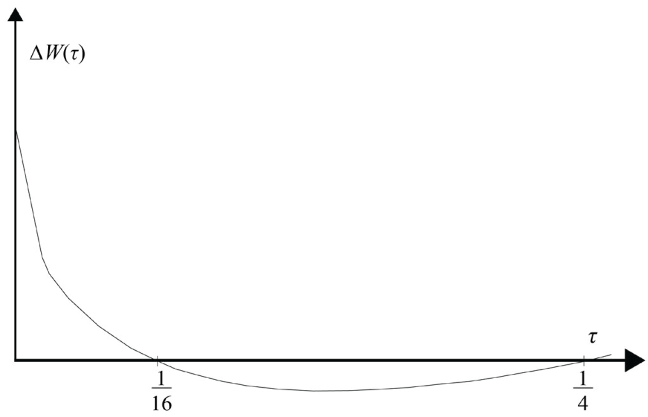
Welfare is given by the sum of π_t and CS_t which can be simplified to

$$W_t = \frac{1}{2} + \tau - \frac{3\sqrt{\tau}}{4} \tag{16}$$

We can write another equation for the difference in welfare between price discrimination and the benchmark monopoly market, $\Delta W = W_t - W_o$. Since this difference depends on the level of profiling employed by the monopolist, which in turn depends on the level of τ, we can write this new equation as a function $\Delta W(\tau)$. Using Equation (16) and benchmark welfare level W_o in Section 2, we get the expression for $\Delta W(\tau)$,

$$\Delta W(\tau) = \frac{1}{8} + \tau - \frac{3\sqrt{\tau}}{4} . \tag{17}$$

FIGURE 1. Curve of $\Delta W(\tau)$ which represents the difference $W_t - W_o$



Over the range $\tau \in [0, 1/4]$, it is clear from Propositions 2 and 3 how price discrimination impacts profits and consumer surplus. Monopoly profits increase while consumer surplus decreases. However, as can be observed in Equation (17), the impact of price discrimination on total welfare is not linear and will depend on the level of τ. This is precisely because of the opposing effect of price discrimination on the two components of total welfare. We can use Equation (17) to identify the range of τ where price discrimination is welfare increasing and where it is welfare decreasing. If for some range of τ, $\Delta W(\tau) > 0$, then we say that in that range of τ, price discrimination is welfare increasing in that range. Similarly, if for some range of τ, $\Delta W(\tau) < 0$, then price discrimination is welfare decreasing in that range. From this, we have the following result:

Proposition 4. *If* $\tau < 1/16$ *then price discrimination results in welfare improvement compared to benchmark monopoly. If* $\tau > 1/16$ *then price discrimination results in inferior welfare compared to benchmark monopoly.*

To demonstrate Proposition 4, note that the function $\Delta W(\tau)$ is a U-shaped curve over τ as shown in Figure 1. Notice that for the range $\tau < 1/16$, the function is positive, which means that price discrimination results in higher overall welfare compared to benchmark monopoly. On the other hand, when τ is in the range (1/16, 1/4) , ΔW is negative, which implies that for this range of τ, price discrimination results in a loss in total welfare compared to welfare in the benchmark case. In equilibrium with price discrimination, we can ignore the values of cost parameters above 1/4 since the monopolist will not find it profitable to price discriminate when τ exceeds 1/4 . In this case, the benchmark monopoly welfare holds. From this, another important result can be inferred.

Proposition 5. *If* $\tau \epsilon$ (1/16, 1/4), *the monopolist's decision to track and price discriminate will result in total welfare loss,* $W_t < W_o$.

Proposition 5 highlights that welfare-decreasing price discrimination may result in equilibrium if profiling cost is sufficiently high but not high enough to completely discourage profiling. In the case where $\tau \epsilon$ (1/16, 1/4), the monopolist will find it profitable to use the profiling technology since profit from price discrimination is still higher than from uniform pricing e.g., $\Delta\pi > 0$. However, in this case, the loss in consumer surplus due to price discrimination is higher than the gains in profit of the monopolist versus the benchmark case.

To be precise, in the range $\tau \epsilon$ (1/16, 1/4), $|\Delta CS| > \Delta\pi$ (where $\Delta CS = CS_t - CS_o < 0$); welfare is inferior versus the benchmark case. Put alternatively, an increase in τ increases consumer surplus, but this increase is less than the decrease in profits, resulting in a net decline in total welfare.

4. Price discrimination and consumer privacy

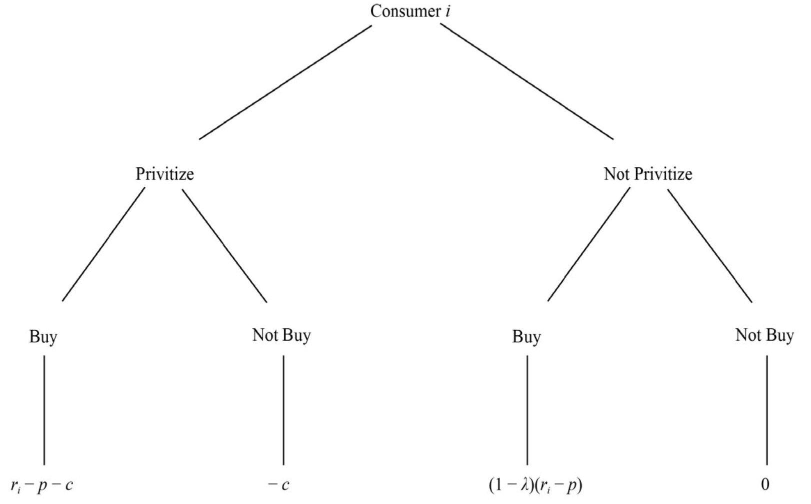
4.1. Privacy decision of consumers

In this section, we will explore a version of the model of Belleflamme and Vergote [2016] developed above with the additional assumption that consumers can now utilize a technology that allows them to privatize and become anonymous to the monopolist. The valuation of consumers who decide to use this privacy technology becomes completely unobservable and, therefore, cannot be price discriminated by the monopolist. However, the technology is not free and consumers must incur a cost $c > 0$ to prevent consumer profiling.

We will consider a model where in the first stage, the firm chooses the level of profiling and uniform price level. In the second stage, consumers observe the profiling decision of the firm and decide whether to privatize or not. Price offers are only made known in the third stage. Those who did not privatize may fall into two groups with two different types of price offers. First, the consumers who are tracked are offered a discriminatory price. The second group consists of those who did not privatize but were not tracked and, therefore, will be offered the good at the uniform price level. The fourth stage is the consumption stage where consumers decide to buy or not.

It follows from this timing that each consumer must condition the decision to privatize or not based on profiling and uniform price expectations. In the fourth stage, consumers will only consume if the utility of buying the good is higher than not buying given their decision to privatize or not from the previous stage. For consumers who choose to privatize, consumers will buy if $r_i - p - c > - c$ since the privacy cost has already been incurred. Notice that it is possible for a privatizing consumer to buy the good even at negative utility just to cover some of the privacy cost c. This happens when $c > r_i - p > 0$, where the surplus from paying a uniform price p can partially cover the cost c. Obviously, a consumer who hid and only bought in the third stage to cover the losses from privatizing is not in his equilibrium strategy. In the case of a consumer who decided not to privatize, the buying is optimal if $r_i - \lambda r_i - (1 - \lambda)p$. This can be simplified to $(1 - \lambda)(r_i - p) > 0$. Since $\lambda \in [0, 1]$ in equilibrium, these condition translates to $r_i > p$ which says that a non-privatizing consumer will automatically buy if offered a price-discriminatory rate equal to his reservation price or if the uniform price is lower than his reservation price. Figure 2 depicts the consumer decision tree.

FIGURE 2. Consumer *i*'s decision tree



From Figure 2, we can already eliminate the path (Privatize, Not Buy) as an equilibrium strategy. This is because any consumer who does so is better off not privatizing and having an expected utility of $(1 - \lambda)(r_i - p)$. Thus, in equilibrium, the decision whether to use the privacy technology is based on whether the expected utility in doing so is at least as high as the expected utility from not privatizing, that is

$$r_i - p_E - c \geq (1 - \lambda_E)\,(r - p_E\,) \tag{18}$$

where p_E are the expected uniform prices to be charged by the monopolist to those it was not able to profile. The term λ_E, on the other hand, represents the expectation with respect to the monopoly profiling choice.[7] The left-hand side of the Equation (18) is the utility from privatizing and paying the expected uniform price while the right-hand side is the expected utility when the consumer decides

[7] The formulation of Equation (18) is similar to that of Belleflamme and Vergote [2016].

not to privatize. Simplifying the inequality in (18) gives us the cut-off valuation, r_c, of those who will be using the technology given the expected price p_E and expected level of profiling λ_E. Then consumer i will privatize if his reservation price satisfies the following inequality

$$r_c \geq p_E + c/\lambda . \tag{19}$$

The mass of consumers who will privatize is given by $1 - p_E - \lambda c$. Notice that the mass of consumers who will opt to privatize given a price expectation is decreasing in c, which implies that the fewer consumers privatize the higher its cost is. On the other hand, the cut-off is decreasing in the level of reach λ, which implies that the higher the reach, the higher the number of consumers who will use the privacy technology. This is because the higher the level of reach chosen by the firm, the more likely they are going to be offered a personalized price, which in turn makes privatizing more attractive. Notice also that the higher the expected uniform price p_E, the fewer are consumers who will choose to privatize. This is because the higher the expected uniform price, the lower the incentive to privatize over being offered a discriminatory price. We assume that all consumers share the same expectation on the uniform price, i.e., all consumers have the same p_E.

Notice also that there is a level of cost, c that makes the threat of consumer privacy binding to the monopolist. Recall that the maximum valuation present in the market is $r = 1$. If c is sufficiently costly such that

$$1 < p_E + c/\lambda^* , \tag{20}$$

then no consumer will find it optimal to privatize and the monopolist can optimally set its profiling to λ^* as if privacy technology did not exist. It also follows in that case that $p_E = p_o = 1/2$. Substituting this price level and solution to λ^* from Equation (10), into Equation (20) then we can derive an expression in terms of price expectation and τ,

$$c > 1/2 - \sqrt{\tau} . \tag{21}$$

We will denote the right-hand side of the inequality as c_m. If the cost of privacy is higher than the threshold c_m, then the monopolist can very well ignore the existence of privacy technology in its decision process.

This is because the cost of privacy is already prohibitively high for any consumer to use.[8] Our primary interest is in cases where c is low enough such that the threat of consumers privatizing is binding and affects the firm's profiling decision. Thus, we impose the condition that

$$0 < c < 1/2 - \sqrt{\tau} . \tag{22}$$

[8] The no-consumer-privacy model in Section 1 can be interpreted as a case of prohibitively costly privacy.

Since c is positive, it must also be the case that

$$\tau < 1/4 \tag{23}$$

The profit of the firm in the presence of a privacy option denoted as π_c, is derived in Appendix A.2 and can be expressed as

$$\pi_c(p, \lambda) = \begin{cases} p(1-p) + \dfrac{\lambda p^2}{2} + \dfrac{c^2}{2\lambda} + \dfrac{\tau\lambda}{1-\lambda} & \text{if } p + \dfrac{c}{\lambda} \leq 1 \\ \dfrac{\lambda}{2} + (1-\lambda)\,p(1-p) - \dfrac{\tau\lambda}{1-\tau} & \text{if } p + \dfrac{c}{\lambda} > 1 \end{cases} \tag{24}$$

In general, the profit depends on four variables: the monopolist's choice of uniform price level p_o and reach λ, the profiling cost parameter τ, and the cost of privacy technology c. The top expression in Equation (24) when $p + (c/\lambda) \leq 1$ corresponds to the case where p is low and λ is high such that some consumers opt to privatize. But as p increases and/or λ decreases such that $p + (c/\lambda) > 1$, privatizing becomes unattractive to all consumers. The profit in this case is given by the bottom part of Equation (24). The behavior of the profit function will be discussed in the next section.

4.2. Equilibrium analysis

4.2.1. Equilibrium λ and p with consumer privacy

We solve the Subgame Perfect Nash Equilibrium with respect to firm pricing and profiling strategy and consumers' decision to privatize. The equilibrium outcome will be summarized by the profile consisting of the uniform price level, profiling level, and the mass of consumers who will decide to privatize and will be denoted as the ordered set (p_c, λ_c, N_c) respectively. Note that the mass of privatizing consumers N_c can be calculated given the level of uniform price and profiling according to Equation (19).

The monopolist chooses the uniform price level and profiling reach that maximizes its total profit given the expectation of the consumers. The privatizing decision of the consumer on the other hand must provide the maximum possible utility during the consumption period. In equilibrium, expectations must be met such that,

$$p_E + c/\lambda_E = p_c + c/\lambda_c \tag{25}$$

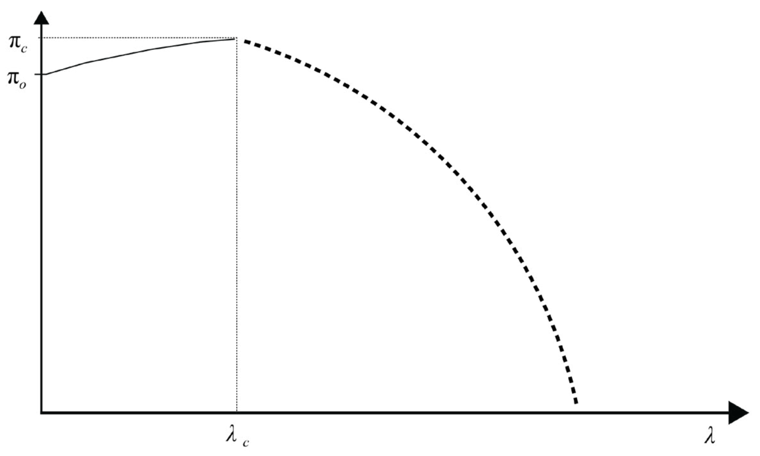
where p_c and λ_c are equilibrium levels as set by the profit-maximizing monopolist. The condition requires that the consumer's uniform price expectation must be correct, $p_E = p_c$ and $\lambda_E = \lambda_c$.

The monopolist strategy in equilibrium must consist of a uniform price level and profiling level that maximizes its profit given its expectation of the consumer decision to privatize. We analyze an equilibrium in this market that corresponds to a relatively expensive profiling cost τ. This results in a low level of profiling where no consumer finds it attractive to privatize.

Notice that at low levels of profiling such that no consumer finds it attractive to privatize i.e., $p + (c/\lambda) > 1$, $(\partial\pi_c)/(\partial\lambda) > 0$. Hence, the firm can increase its profit by increasing its profiling reach in this region. This region is represented by the solid curve in Figure 3 where λ is less than λ_c. As long as the firm increases its profiling level within this region, it can increase the number of consumers offered the discriminatory price without pushing consumers into privatizing. Since total profiling cost increases at a slower rate at low levels of λ, the increase in reach of profiling below λ_c results in higher profit.

However, when the profiling cost parameter τ is sufficiently high such that for $p + (c/\lambda) \leq 1$ then profit will start to decrease once λ increases beyond λ_c as in Figure 3. Like before, this higher level of profiling cost increases the price discriminatory segment which increases revenue. However, in this region, the high level of profiling cost already drives some high-valuation consumers to privatize. Additionally, the cost of profiling increases much faster at these levels of profiling. These two forces result in lower profits as λ increases.

FIGURE 3. Profit function of the monopolist with consumer privacy



Thus, the level of λ that maximizes the firm's profit is where the two segments of the curve meet in Figure 3, where $p + \lambda_c = 1$. We provide the following results for the profit-maximizing level of λ and p, which we derive in Appendix A.2.

Proposition 6. *If* τ is sufficiently high such that $\partial\pi_c/\partial\lambda > 0$ for $p + \lambda^c > 1$, *then in equilibrium* $\lambda_c(c) = 4c/(1 + \sqrt{c^2 - 6c + 1} + c)$ and the optimal price level is $p_c(c) = (3 - \sqrt{c^2 - 6c + 1} - c)/4$.

We add the following result on the consumer privatizing decision.

Proposition 7. *If τ is sufficiently high such that $\partial\pi_c/\partial\lambda > 0$ for $p + (c/\lambda)$, then no consumer privatizes, that is $p_c + (c/\lambda_c) = 1$.*

Figure 4 shows the behavior of λ_c and p_c as a function of privacy cost c. First, notice that λ_c is increasing in c. In equilibrium, the firm chooses a higher λ_c the more expensive it is for consumers to privatize. This is because a higher cost of privacy prevents more consumers from using the technology. This in turn allows the firm to profitably track more consumers with less fear that they are going to privatize their valuation. Second, the uniform price level p_c is also increasing in c. Recall that that higher c results in higher λ_c which encourages some high-valuation consumers to privatize. To prevent this privatizing in the face of higher λ_c, the monopolist uses a higher uniform price level p_c to *penalize* privatizing. To understand this *penalty*, recall that consumers privatize to avoid price discrimination and instead get a uniform price offer. A higher uniform price, therefore, makes privatizing less attractive for any given level of λ_c.

4.2.2. Effect of privacy technology on the aggressiveness of firm profiling and the uniform price level

We now turn to the question of how the availability of privacy technology impacts the decision of the monopoly when consumers do not have the option to privatize their information. To answer this, we also present in Figure 4 the *no-privacy* level of profiling λ^* derived in Section 3.2. We also include in Figure 4 the upper limit c_m from Equation (21) as the vertical line $c_m(\tau)$. We can identify the level of λ^*, represented by the horizontal line in Figure 4, by noting that $\lambda^* = 2c_m(\tau)$. Hence, for any given value of τ, we can determine $c_m(\tau)$, which in turn allows us to determine λ^*. We will show that the presence of privacy technology leads to less aggressive consumer profiling and price discrimination depending on its *affordability*, that is, the level of c.

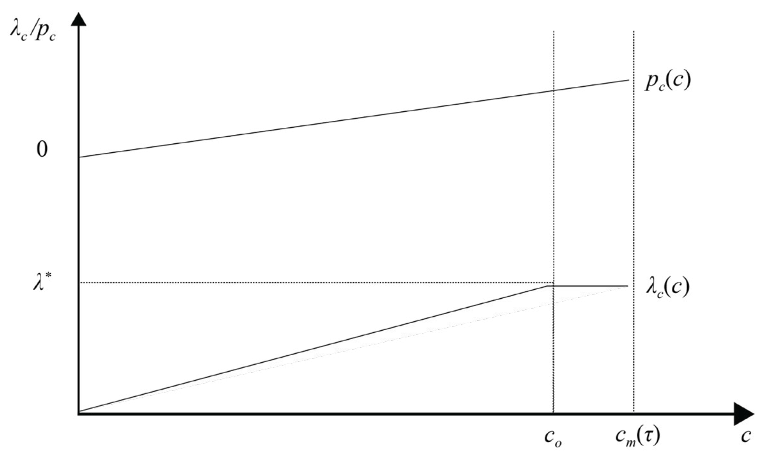
The level c_o is the level of privacy cost where $\lambda_c = \lambda^*$ and where λ_c starts being flat at λ^*. Notice that in Figure 4, when $c < c_o$, then $\lambda_c < \lambda^*$, that is, the level of profiling when privacy is an option is lower than when privatizing is not available to consumers. This means that as long the privacy technology is sufficiently cheap, it can reduce the level of profiling, and thus, the incidence of price discrimination by the monopolist. Furthermore, although no one uses the privacy technology in equilibrium, the privacy technology serves as a *deterrent* against more aggressive profiling and price discrimination.

However, when the privacy cost c is sufficiently high such that $c \geq c_o$ in Figure 4, then $\lambda_c = \lambda^*$. This means that if the privacy technology is relatively expensive, the monopolist chooses a level of profiling equal to the case when privacy technology is not available to consumers. This is represented by the flat region of the λ_c curve in Figure 4. In this case, the presence of technology does not result in less profiling by the monopolist. Notice that in this case, while $\lambda_c = \lambda^*$, the uniform price is higher than before . This implies that the privacy technology can only lessen the profiling and number of consumers' price discriminated against if privacy is sufficiently cheap (i.e., $c < c_o$); otherwise, the privacy technology only results in the same level of profiling, but a higher uniform price level.

We summarize these results in the following proposition.

Proposition 8. *If the privacy cost is sufficiently low, $c < c_o$, then the presence of privacy technology results in less aggressive profiling of the monopoly. However, a sufficiently expensive c, $c > c_o$ results in profiling that is as aggressive as in the case where privacy technology is unavailable to consumers, but with a higher uniform price level.*

FIGURE 4. Equilibrium profiling and price level



This result agrees with the finding of Bellefamme and Vergote [2016] for markets with an exogenous level of profiling. Their result shows that privacy technology may increase uniform price levels in markets where the firm has a fixed and exogenous level of λ.

4.3. Equilibrium impact of less costly profiling technology

Another relevant question we will answer concerns the impact of decreasing profiling cost parameter τ, perhaps due to improvements in consumer profiling technology. Since a lower τ decreases the cost of profiling, one might expect that a lower τ should generally increase λ_c in equilibrium. However, the results of the analysis show that whether a decrease in τ increases λ depends on the level of privacy cost c.

The impact of less costly profiling is graphically presented using Figures 5 and 6. What we find is that a lower profiling cost parameter τ may result in more aggressive profiling only if c is sufficiently high. Otherwise, changes in τ will not impact λ_c. To see this, consider a case where we have an initial level of τ such that the upper bound of c is c_m in Figure 5. Suppose also that the current cost of privacy is c_1 such that $c_1 < c_o$ in Figure 5. This level of privacy cost c_1 implies a level of profiling equal to λ_c as in Figure 5. Now, suppose τ declines, which implies less costly profiling, increasing the monopolist's capacity to track. This increases $c_m(\tau)$ from c_m to c_m'.[9] The increase in threshold privacy cost is due to the fact that consumers are now willing to pay a higher privacy cost due to the higher capacity of the monopolist to track. Recall from Equation (10) that this decrease in τ increases the profiling reach had there *been no privacy technology* from λ_1^* to λ_2^* in Figure 5. This change increases c_o to c_o' and extends the upward-sloping region of the λ_c^o curve from the dashed curve λ_c^o to include the solid portion λ_c^1. The new curve representing the optimal level of profiling is now λ_c^1 which only starts to flatten at λ_2^* in Figure 5. Notice that if privacy cost is at c_1, this change brought by lower τ does not impact the level of profiling which stays at λ_c. Thus, as long as c is below the threshold c_o, less costly profiling will not impact the aggressiveness of profiling. This is because with low c, consumer privacy is a threat and the firm will find it unprofitable to expand consumer profiling even with declining profiling cost parameter τ.

However, notice the alternative case where the initial level of c is greater than c_o as in $c_1 > c_o$ in Figure 6. With the initial value of τ and the original dashed λ_c^o curve, the optimal level of profiling is $\lambda_c = \lambda_1^*$. Consider again a decline in τ such that c_m increases to c_m'. This again extends the curve for the optimal level of profiling that is now given by the λ_c^1 curve. The new optimal level of profiling implied by c_1 is now λ_c', which is greater than the previous λ_1^*. This result suggests that if the privacy technology cost c is sufficiently high, the firm will find it optimal to increase profiling when it becomes less costly. This is because when c is costly, the firm has more ability to increase its profiling aggressiveness without the threat of some consumers privatizing. However, when privacy cost is sufficiently cheap such as c_1, even a less costly profiling will not increase λ.

Thus, in equilibrium, the impact of the declining cost of profiling will depend on how costly privacy is as measured by c. We summarize the result in the following proposition.

Proposition 9. *A lower τ will increase the profiling if $c > c_o$; otherwise, a decrease in τ will not impact the level of profiling.*

[9] We suppress the functional notation $c_m(\tau)$ to declutter the diagram and instead just use c_m and c_m'.

FIGURE 5. Effect of lower τ on λ^* and λ_c when $c < c_o$

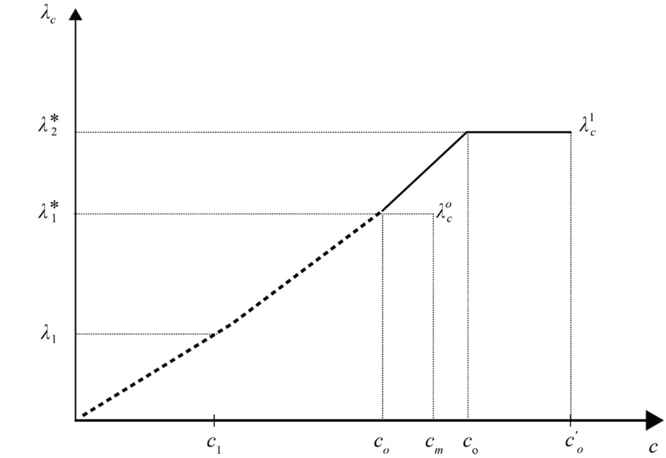
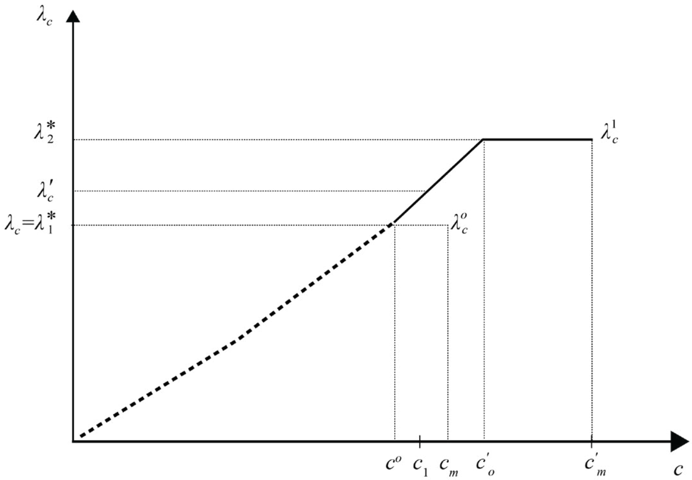


FIGURE 6. Effect of lower τ on λ^* and λ_c when $c > c_o$



5. Summary

Driven by developments in technology that allow the extraction of individual-level consumer information, this paper analyzed the impact of price discrimination and consumer privacy decisions on market outcomes. We considered two scenarios: (1) a case where consumers have no option to privatize their information and (2) a costly privacy technology exists that allows consumers to privatize and prevent profiling by the monopolist.

Absent the availability of privacy technology that protects consumers from monopoly profiling, we find that consumers generally lose due to price discrimination. This theoretical result is well-known and forms the basis of the general aversion towards price discriminatory practices. Because the monopolist only tries to maximize its profit, it may pursue price discrimination even if the strategy results in lower total welfare. Our analysis showed that this happens if consumer profiling is sufficiently cheap for the monopolist but is expensive enough from the viewpoint of total welfare.

Turning to the case where consumers have the option to use privacy technology, we find that the monopolist chooses a consumer profiling reach and uniform price level such that consumers find no incentive to privatize. This results in an equilibrium where no consumer chooses to use the privacy technology. Although no consumer privatizes their information, the privacy technology may reduce monopoly profiling if privacy costs are sufficiently low. This leads us to an important result: privacy acts as a *deterrent* against price discrimination only if it is *sufficiently inexpensive* for consumers. However, if privacy is sufficiently costly, results show that the monopolist tracks consumers as aggressively as in the case when privacy was not an option. For the uniform price level, the attempt of the monopolist to discourage privacy induces it to charge a higher uniform price level compared to when privacy was not an option for consumers. This result about the uniform price level is true for all positive levels of privacy costs.

Lastly, we analyzed the impact of cheaper consumer profiling on the profiling reach decision of the monopolist. We find that a cheaper profiling cost will only induce more aggressive profiling if privacy cost is sufficiently high such that consumer privatizing is not much of a threat. Otherwise, with a sufficiently inexpensive privacy cost, a cheaper profiling cost will not change the monopolist's choice of its profiling reach.

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Appendix

A.1. Expected revenues from profiled and unprofiled segments

We first derive the expected revenue from the profiled segment. Let L_t be the set of profiled consumers after deciding to use the profiling technology. The size of this set L_t is λN. The total number of possible sets L_t with size λN that can be drawn from the population is given by the expression.

$$C, (N, \lambda N) = \frac{N!}{\lambda N!\ (N - \lambda N)!} \tag{A.1}$$

Thus, for any given λ, only one out of $C(N, \lambda N)$ combinations of profiled consumers will be actualized. We denote the set of all possible L_t as Λ.

For a given actualized set of consumers profiled $L_t \epsilon \Lambda$, the revenue R_t by charging their reservation prices, is

$$R_t = N\int_{i\epsilon L_1} r_i f(r)dr \tag{A.2}$$

The expected revenue in the case of continuous reservation can be calculated using the following process.[10] Let $g(x)$ be a function of a random variable x and $f(x)$ be the probability density function of x. Then

$$E(g(x)) = \int_{-\infty}^{\infty} g(x)f(x)dx\ . \tag{A.3}$$

Letting $g(x) = R_t(r_i)$, then the expected revenue is given by

$$E(R_t|\lambda) = \int_0^R [N\int_{i\epsilon L_t} r_i f(r)dr]\, f(r)dr \tag{A.4}$$

Interchanging the order of integration, we get

$$E(R_t\ \lambda) = N\mu_r \int_{i\epsilon L} f(r)dr\, . \tag{A.5}$$

Since the proportion of consumers profiled with respect to the total size of the market is λ, the following statement must also be true

$$\lambda = \int_{i\epsilon L_t} f(r)dr = \sum_{i\epsilon L_t} \int_a^b f(r)dr \tag{A.6}$$

for all a, $b \epsilon [0, R]$ such that all i, i.e., consumers with valuations in the interval $[a, b]$ are members of L_t. Thus, (A.5) reduces to

$$E(R_t|\lambda) = \lambda N\mu_r\, . \tag{A.7}$$

Note that the expressions above indicate that the expected revenue is the mean of valuation of the whole market multiplied by the number of individuals profiled.

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[10] The underlying principle behind this process is more commonly known as The Law of the Unconscious Statistician [Ross 1980].

This expectation does not depend on any particular L_t but is fully characterized by the mean and total number of consumers profiled.

The result in (A.7) makes more intuitive sense if we consider discrete r_i. Like before, the revenue will be

$$R_t = \Sigma_{i\epsilon L_t} r_i \tag{A.8}$$

Getting the expectation of (A.8) we get

$$E(R_t|\lambda) = E(\Sigma_{i\epsilon L_t} r_i) \tag{A.9}$$

Invoking the linearity of expectations over summation operation

$$E(R_t|\lambda) = \Sigma_{i\epsilon L_t} E(r_i) \tag{A.10}$$

since there are λN consumers profiled, the expectation is reduced to

$$E(R_t|\lambda) = \lambda N \mu_r \tag{A.11}$$

(A.7) and (A.11) imply that the firm, before any actual set of consumers is profiled, has an expected value of revenue from profiled consumers equal to $\lambda N \mu_r$.

The second part of the revenue of the firm comes from the unprofiled segment. This segment is composed of consumers whose reservation prices are unknown to the firm. The price offered to this segment is p and is uniform. The size of this segment is $(1 - \lambda)N$. However, out of $(1 - \lambda)N$ consumers in this segment, only those with valuations equal to or above p_o are going to buy from the firm. Let $P(H)$ and $P(L_t^{'})$ be the probabilities that a consumer has a valuation higher than p_o and that the consumer is unprofiled respectively. Assuming that the chances of one being profiled does not depend on his/her valuation, then the probability that a consumer is both unprofiled and has a valuation above p_o is given by the expression:

$$P(H \cap L_t^{'}) = P(H)P(L^{'})\,. \tag{A.12}$$

Noting that $P(H) = \int_{p_o}^{R} f(r)dr$ and $P(L^{'}) = (1 - \lambda)$, then

$$P(H \cap L^{'}) = (1 - \lambda) \int_{p_o}^{R} f(r)dr\,. \tag{A.13}$$

The expected revenue R_o from this segment is therefore

$$R_o = (1 - \lambda)N \int_{p_o}^{R} p_o f(r)dr\,. \tag{A.14}$$

A.2. Derivation of profit function with consumer privacy technology

The profit of the monopolist, given the levels of c and τ, is function of the uniform price level it charges, p, and of the profiling level, λ. The profit function will have two parts.

First, notice that if the levels of p and λ are such that some consumers are privatizing, i.e., $p + (c/\lambda) < 1$, then the profit of the monopolist can be decomposed into four distinct sources:

a. Low-valuation consumers who are **profiled** with profit $\lambda\int_o^p rdr$.
b. *Non-privatizing consumers* with valuations between $[p, r_c]$ who are **profiled** with profit $\lambda\int_p^{r_c} rdr$.
c. *Non-privatizing consumers* with valuations between $[p, r_c]$ who are **not profiled** and charged the uniform price level p with profit $(1-\lambda)p\int_p^{r_c} rdr$.
d. *Privatizing consumers* with valuations between $[r_c, 1]$ charged the uniform price level p with profit $(1-\lambda)\, p\int_{r_c}^1 dr$.

Noting that $r_c = p + \lambda c$, adding profit from these sources results in $\pi = p(1-p) + (\lambda p^2/2) + (c^2/2\lambda) - (\tau\lambda/1-\lambda)$ if $p + (c/\lambda) < 1$.

This is the first part of our profit function in Equation (24).

The second part of the profit function is obtained when $p + (c/\lambda) = 1$. In this case, no consumer privatizes and there are only two sources of profit for the monopolist. First, it derives a profit equal to $\lambda\int_0^1 rdr$ from those it was able to track and price discriminate. Second, those who are not tracked and charged their reservation price are offered the goods at a uniform price level p. From this second segment, the monopolist gets profit equal to $(1-\lambda)\, p\int_p^1 dr$. Adding these two sources gives us $(\lambda/2) + (1-\lambda)\, p\,(1-p) - (\tau\lambda/1-\lambda)$. This is the second part of the profit function in Equation (24) if $p + (c/\lambda) = 1$.

A.3. Derivation of profit-maximizing level of profiling and price levels

We know that the maximum profit is obtained when $p + (c/\lambda) = 1$, i.e., when the monopolist squeezed every consumer out of privatizing. Thus, a strategy to derive the equilibrium values of p and λ is to maximize profit and impose the condition that no consumer privatizes.

To do this, we differentiate the relevant section of the profit function in Equation (24) with respect to p, the variable where the function is continuous when $p + (c/\lambda) = 1$, and equate it to zero. We get

$$\frac{d\pi_c}{dp} = 1 - 2p + \lambda p = 0 \cdot \tag{A.15}$$

Note that $p + (c/\lambda) = 1$ also implies that $\lambda = (c/1-p)$. We substitute this expression to Equation (A.15). Solving for the optimal level of p yields $p_c = (3-\sqrt{c^2 - 6c + 1} - c)/4$. Substituting this to the equation $p + (c/\lambda)$ gives us the optimal level of λ which is $\lambda_c = 4c/(1 + \sqrt{c^2 - 6c + 1} + c)$. These expressions for p_c and λ_c are the same given in Proposition 6.

The Philippine Review of Economics
62(1):27-55. DOI:10.37907/2ERP5202J

Forecasting currency in circulation with the central bank balance sheet

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Currency in circulation (CIC) is an important variable in monetary policy as it affects liquidity and guides the currency issuance operations of central banks. This paper proposes a novel approach to forecast CIC using central bank balance sheet variables, namely assets and liabilities other than currency issued. The balance sheet approach is able to generate monthly CIC forecasts as opposed to demand-for-currency models anchored on quarterly Gross Domestic Product (GDP). This allows for more responsive currency policy, particularly during crisis periods when precautionary motives intensify—reflected in a decoupling of GDP and CIC—or when spikes in currency demand arise due to heightened transaction motives.

Dynamic time series regression models are estimated to operationalize the balance sheet approach and are compared to baseline predictive methods such as Error-Trend-Seasonality (ETS) models, Autoregressive Integrated Moving Average (ARIMA), and seasonal naïve methods. Results show that including balance sheet variables significantly improves the predictive ability of CIC models in terms of mean absolute percentage error (MAPE) and root mean squared scaled error (RMSSE). These findings hold across multiple training and test sets through time series cross-validation, suggesting stability of forecast accuracy results.

JEL classification: E41, E47, C22
Keywords: currency in circulation, central bank balance sheet, time series analysis

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1. Introduction

The *Bangko Sentral ng Pilipinas* (BSP) is the sole issuer of the domestic currency, pursuant to Republic Act (RA) No. 7653, as amended by RA No. 11211. Thus, the BSP is mandated to provide the Philippine economy's currency requirements, while retiring unfit currency from circulation. The activities encompassing the cash cycle—from forecasting demand to retiring unfit currency—are some of the most notable and unique functions of a central bank. To successfully fulfill this mandate, central banks ought to accurately forecast the total amount of currency circulating in the economy.

This paper proposes an alternative way to model and forecast currency in circulation (CIC) based on the balance sheet of a central bank. An expansion in a central bank's assets would be offset by an equivalent increase in its reserve money liability. For example, foreign exchange inflows, when exchanged into domestic currency, expand overall liquidity in the system. To the extent that the expansion affects the inflation target, the excess liquidity is mopped up through open market operations. The unsterilized portion of the expansion in liquidity is kept as deposits in banks or withdrawn as cash, thereby increasing CIC.

To demonstrate this modeling approach, assets and liabilities other than currency issued (LOTCI) of the BSP are used to predict CIC. This methodology departs from the usual demand-for-cash framework, which treats transaction motives, precautionary motives, and opportunity costs in holding cash as determinants of CIC. One advantage of this novel approach is that monthly CIC forecasts may be generated as it utilizes central bank balance sheet data, which are available monthly. This is in contrast with demand-for-cash models which rely on Gross Domestic Product (GDP), limiting forecasts to quarterly intervals.[1]

From a policy perspective, adopting a higher-frequency model can more effectively inform a central bank's liquidity provisioning activities, particularly the issuance of notes and minting of coins, which are highly sensitive to economic shocks and shifts in consumer behavior. This approach is especially valuable during crises when GDP and CIC can become decoupled (e.g., GDP falls while CIC rises) due to heightened precautionary motives. High-frequency CIC can thus serve as a useful indicator of consumer confidence and purchasing behavior during periods of economic stress.

In the broader context of monetary policy, CIC forms the foundation of the money supply and plays a key role in central bank decisions to inject or withdraw liquidity from the economy, whether through repurchase agreements, foreign exchange swaps, or other liquidity management tools. Additionally, CIC influences the transmission of monetary policy, as changes in the policy rate affect how economic agents spend, borrow, and save through the banking system.

[1] The potential use of mixed-frequency CIC models to combine quarterly and monthly demand-for-cash variables, as well as balance sheet variables, is discussed in Section 8.

An increase in CIC may signal growing informality in economic activity, which can weaken the effectiveness of monetary policy as consumers and firms either bypass or lack access to the banking system [Ospina 2023]. This dynamic is particularly relevant in developing countries like the Philippines, where a large share of transactions is still carried out in cash. All told, the proposed models may complement the BSP toolkit in forecasting and managing CIC, better informing its currency policy and overall monetary policy.

2. Demand-for-currency and alternative approaches to CIC estimation

The currency requirements of the economy can be better understood with the demand-for-currency framework. This is motivated by the fundamental functions of currency in an economy, namely as: (a) unit of account, (b) store of value, and (c) medium of exchange. Given these functions, Shirai and Sugandi [2019] argued that the motivations for holding cash are driven by the following factors:

- **Transaction motive** – cash is used as payment for goods and services such that the demand for cash is positively related to economic activity, typically proxied by GDP;
- **Opportunity cost** – cash holdings are weighed against financial returns arising from cash substitutes like demand deposits. Larger opportunity costs (e.g. higher retail deposit rates or higher inflation rates) lower the demand for cash;
- **Precautionary motive** – cash ensures liquidity in times of crises so demand for cash increases during times of uncertainty or when investor risk appetite falls;
- **Other motives** – demographic factors may affect cash holdings as aging populations may prefer to hold cash.

Given this framework, CIC is often forecasted based on macroeconomic variables that capture demand-side factors. GDP accounts for the transaction motives, while inflation and interest rates proxy the opportunity costs to hold cash. Exogenous interventions are also introduced to consider market shocks over time. Autoregressive Integrated Moving Average Models with Exogenous Variables (ARIMAX) and Vector Autoregressive (VAR) Models are commonly deployed to model CIC following the theory of demand-for-currency [Khatat 2018].

Most central banks generate quarterly CIC forecasts consistent with the frequency of GDP measurement. ARIMAX and cointegrating regression models have also been deployed to predict the levels of CIC, and potentially model long-run relationships among variables. For instance, the Bank of England utilizes an error correction model to estimate the relationship between CIC and macroeconomic and currency management variables including nominal consumption, interest rates, exchange rates, the unemployment rate, the number of bank branches and post offices, and the number of regular payments made in cash per person per year, among other factors [Miller 2017]. This model performs well in longer forecast horizons but leads to larger forecast errors in the short run relative to a simple autoregressive model. This may be due to omitted variable bias or incorrect specification of the econometric model. The authors note that inaccuracies may arise as the input variables to the error correction model are extrapolated to arrive at the final CIC forecast.

Prayoga, Suhartono, and Rahayu [2017] note that CIC in Indonesia is influenced by Eid al-Fitr.[2] To account for this factor, an ARIMAX model was used to forecast CIC. They also estimated a hybrid model of ARIMAX and artificial neural networks (ANN) to model potential non-linearities in the data. By leveraging ANN, the hybrid model was more effective at capturing non-linear patterns over time. Nonetheless, both models were sensitive to outliers, highlighting the potential value of intervention analysis. This sensitivity may also point to overfitting, as the authors observed substantially stronger predictive performance on in-sample data compared to out-of-sample data.

The literature in forecasting CIC also includes univariate models that purely depend on the series' own history. Seasonal Autoregressive Integrated Moving Average (SARIMA) models are commonly deployed to forecast CIC and account for recurrent patterns in the data. Such models have been used in Poland [Kozinski and Swist 2014], the Maldives [Shuaib and Nazeeh 2019], and Qatar [Balli and Elsamadisy 2011]. The European Central Bank has also employed exponential smoothing and ARIMA techniques [Strickland 2015]. These models often perform well in the short term, as they rely on recent historical patterns. However, the lack of structure[3] can result in larger forecast errors in the long run (Balli and Elsamadisy [2011]; Shuaib and Nazeeh [2019]). Moreover, ARIMA models may struggle to capture non-linear dynamics, as they are not designed to model such patterns in time series data.

The *Banca d'Italia* uses a suite of models such as ARIMA, breakpoint regression, ARIMAX, and VAR models. Based on its observation "pure ARIMA models outperform more complicated models in terms of forecast accuracy", as including macroeconomic variables did not translate to better predictive performance [Sasso 2018]. Khatat [2018] further argued that while forecasts from ARIMA tend to be superior compared to pure expert knowledge, combining ARIMA forecasts with expert judgment may significantly improve forecasts to account for unexpected and significant changes.

Khatat [2018] emphasized that "the fundamental longer-run determinants of the demand for cash are distinct from its short-run determinants." In the short run, potentially at a daily frequency, CIC is primarily influenced by factors such

[2] Eid al-Fitr is an Islamic religious holiday celebrated by Muslims to mark the end of Ramadan.

[3] In this sense, structural models refer to time series models that rely on economic theory as opposed to pure time series models that only account for a series' historical behavior.

as the number of weekdays, payroll schedules, holidays, and other calendar effects. In contrast, long-run CIC dynamics are shaped by broader demand-for-money factors, including economic growth, inflation, interest and exchange rates, payment system usage, and the occurrence of economic shocks. As such, different forecasting models may be appropriate depending on the time horizon considered.

In the case of the Philippines, the BSP relies on the demand-for-currency framework to estimate the economy's currency requirements. The BSP, through its Department of Economic Research, first predicts CIC based on macroeconomic variables that reflect the motives to hold cash. In particular, GDP accounts for the transaction motives, while inflation is its measure of the opportunity cost to hold cash. CIC forecasts using macroeconomic variables generate quarterly estimates consistent with the frequency of GDP data reporting.

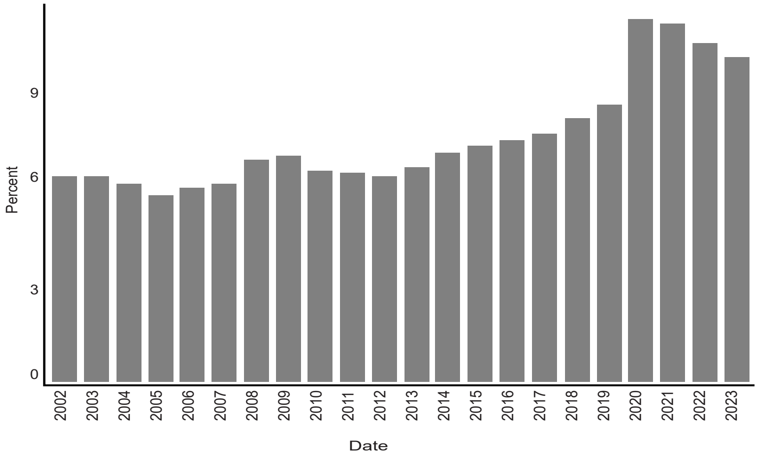
At this stage, the BSP estimates the volume of unfit currency to be retired in order to determine its currency order. Statistical models such as ARIMA and Co-integrating Regression Analysis (CiRA) are utilized. The initial currency order is then adjusted based on the BSP's current inventory and buffer stock requirements to arrive at the final order. This is subsequently broken down by denomination, forming the denominational currency order that ultimately guides the BSP's currency production.

This process highlights how more timely and accurate forecasting of CIC can lead to a better alignment between the BSP's currency order and the economy's actual currency needs. A key limitation of the demand-for-currency framework, however, is that the relationship between GDP and CIC can shift significantly during periods of uncertainty or economic shocks. In stable times, rising GDP requires a concomitant increase in CIC to support the expanding volume and value of transactions. Yet, in times of crisis or heightened volatility, GDP may decline while CIC rises, driven by precautionary motives.

The saying "cash is king" proved especially true during the COVID-19 pandemic, when the CIC-to-GDP ratio surged to 11.4 percent, an increase of 2.8 percentage points year-on-year (Figure 1). In periods of heightened uncertainty, such as this, traditional demand-for-currency models may produce larger-than-usual forecast errors. It is also worth noting that the CIC-to-GDP ratio was calculated by comparing year-end CIC levels to annual nominal GDP.

During times of crisis, higher-frequency CIC forecasts may be necessary to monitor liquidity conditions and assess consumer confidence. Alongside other monthly macroeconomic indicators like inflation, interest rates, and unemployment, CIC can be tracked and forecasted by economic agencies to gauge the pace and extent of economic recovery. These circumstances call for alternative models that do not depend on quarterly GDP.

FIGURE 1. CIC-to-Nominal GDP ratio (2002 to 2023, in percent)



Source: BSP, PSA, Authors' calculations.

In general, CIC models in the literature employ non-structural or "pure" time series forecasting techniques such as ARIMA and exponential smoothing. Time series regression models, on the other hand, incorporate macroeconomic and currency variables that reflect the underlying motives for holding cash, grounded on the demand-for-cash framework. However, there is limited research that models CIC beyond this traditional approach. This paper offers a novel perspective by proposing a method that forecasts CIC through the lens of the money creation process, as reflected in a central bank's balance sheet.

3. Examining the central bank's balance sheet

Another approach to predict CIC is by looking at the demand for local currency emanating from foreign exchange inflows. This entails the examination of the BSP's balance sheet, since whenever it purchases foreign exchange, it effectively sells the local currency, which when left unsterilized could end up as cash circulating in the economy. Examining the BSP's balance sheet, its assets are primarily composed of net foreign assets (NFA),[4] dominated by the country's gross international reserves. Assets are also derived from the BSP's domestic claims (DC) in relation to its transactions with residents.[5] As of the end of August 2024, NFA and DC comprised 91.6 and 8.4 percent, respectively, of the BSP's total assets.

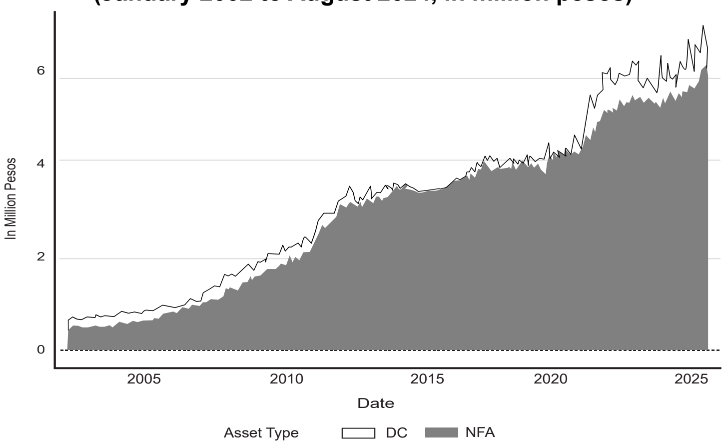
[4] These consist of a) Claims on Non-Residents that comprise the country's official reserve assets and other foreign assets; and b) Liabilities to Non-Residents consisting of gross foreign liabilities segregated into short-term and long-term maturities.

[5] These comprise a) Net Claims on Central Government which consist of securities other than shares and loans less deposit liabilities to CG; b) Claims on Other Depository Corporations such as deposits, securities other than shares, loans, and financial derivatives; and c) Claims on Other Sectors which comprise mainly of loans to other financial corporations, claims on state and local government, claims on public nonfinancial corporations and claims on private sector.

Over the years, the country has received substantial foreign exchange inflows, on the back of strong macroeconomic fundamentals, overseas remittances, and export earnings, contributing to the increase in the BSP's net foreign assets (NFA). Additional liquidity also flowed into emerging economies like the Philippines as a result of unconventional monetary policies adopted by advanced economies following the 2008 Global Financial Crisis. These inflows led to a buildup of international reserves and a further expansion of the BSP's assets. These trends are illustrated in Figure 2.

On the other hand, claims on the central government briefly rose in the time of the pandemic as the BSP granted loans to the national government to help finance its COVID-19 response. This explains the rapid increase in DC in 2020 and 2021. In particular, DC reached ₱360.3 billion at end-2019 (7.6 percent of total assets) and then more than doubled to ₱813.2 billion in December 2020 (13.3 percent of total assets), before settling at ₱783.6 billion in December 2021 (12.3 percent).

FIGURE 2. BSP balance sheet assets (January 2002 to August 2024, in million pesos)



Source: BSP Central Bank Survey (SRF-based), Authors' calculations

Looking at the other side of the balance sheet, CIC is a liability of the BSP and forms part of the reserve money (RM).[6] Other liabilities of the BSP include those

[6] Aside from currency issued, there are other items in the reserve money including:

A. Liabilities to Other Depository Corporations (LODC) which comprise:

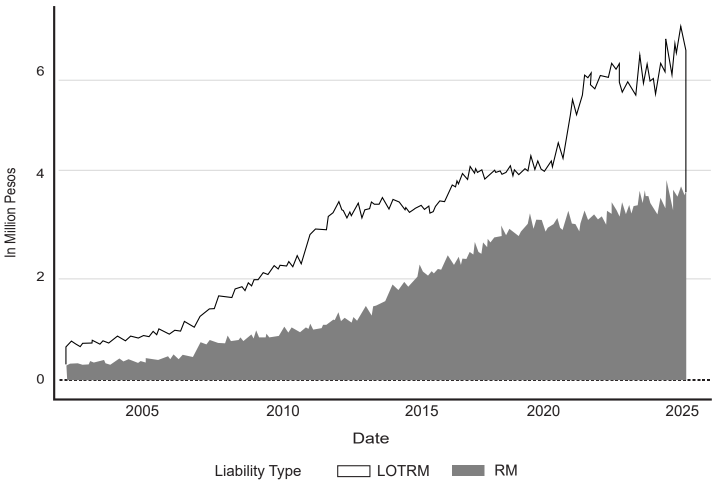
- Required reserves and clearing balances of Other Depository Corporation (ODCs) which refer to the BSP's regular peso demand deposit liabilities to commercial banks, specialized government banks, thrift banks, rural banks and nonbanks with quasi-banking functions and accrued interests.

B. Liabilities to Other Sectors (LOS) consist of:

- Transferable deposits of other financial corporations (OFCs) included in broad money refer to the BSP's demand deposit reserve accounts of Common Trust Funds (CTF) and Trust and Other Fiduciary Accounts (TOFA) of OFCs and accrued interests.
- Reserve Deposit Account of OFCs which pertains to the funds placed with the BSP in lieu of government securities holdings to be bought directly from the BSP in compliance with the liquidity reserve requirement on CTF and TOFA accounts and accrued interests.

derived from the Reverse Repurchase Facility, Overnight Deposit Facility, and Term Deposit Facility,[7] as well as Other Equity and Treasury-International Monetary Fund (IMF) accounts. These types of liabilities can be classified as liabilities other than reserve money (LOTRM).[8] In December 2020, the share of LOTRM to total BSP liabilities rose sharply to 44.4 percent, up from 32.0 percent a year earlier. This shift is aligned with the BSP's expansionary monetary policy aimed at supporting the economy during the pandemic. From 2015 to 2019, the LOTRM-to-liabilities ratio averaged 33.2 percent, compared to an average of 42.2 percent between January 2020 and August 2024. These developments are illustrated in Figure 3.

FIGURE 3. BSP balance sheet liabilities (January 2002 to August 2024, in million pesos)



Source: BSP Central Bank Survey (SRF-based), Authors' calculations

An increase in the BSP's assets from reserve accumulation is mirrored by a corresponding rise in its liabilities, in line with the accounting identity. If unsterilized, this rise, often through reserve money, can be inflationary [Aizenman and Glick 2008]. To manage this, the BSP conducts open market operations and offers deposit facilities to absorb excess liquidity. These tools help align reserve money growth with the inflation target by selling securities (absorbing local currency) and later repurchasing them, or by attracting placements in its deposit facility.[9] In short, the BSP uses open market operations and its deposit facility to sterilize excess liquidity arising from reserve accumulation.

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[7] This was introduced in June 2016 following the implementation of the Interest Rate Corridor (IRC) system.

[8] Liabilities Other Than Reserve Money include all other unclassified accounts such as deposits and securities other than shares, shares and other equity and other items (net).

[9] Likewise, foreign exchange swaps and forward contracts may also be employed to manage liquidity. The costs associated in sterilization, as well in holding international reserves (such as negative carry) is not within the scope of the paper.

Sterilization activities through the Reverse Repurchase Facility, Overnight Deposit Facility, and Term Deposit Facility increase the BSP's liabilities under LOTRM, offsetting the accumulation of assets while moderating inflationary risks. Local currency converted through foreign exchange purchases that are not sterilized could be kept as deposits in banks or could be withdrawn as cash, thereby increasing CIC. Some of the unsterilized assets may also make their way into non-CIC reserve money, such as Liabilities to Other Sectors or Liabilities to Other Depository Corporations (see footnote 6 for more information).

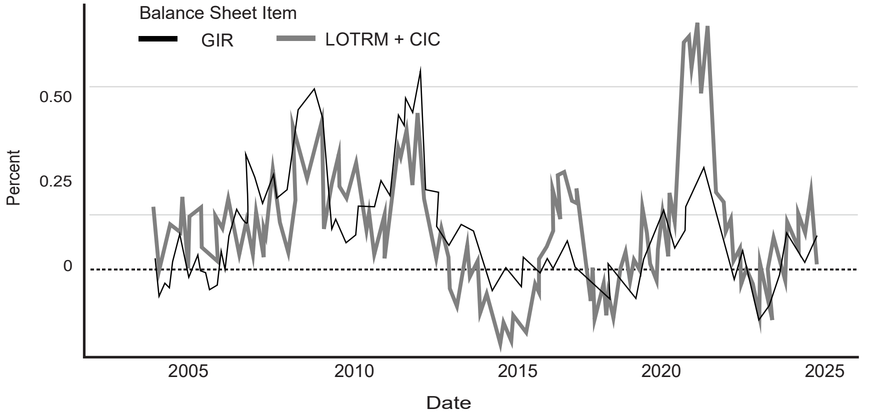
Figure 4 illustrates how CIC is created in a central bank's balance sheet: an expansion in assets through reserve accumulation (e.g., from remittances or export receipts) leads to a corresponding rise in liabilities. This increase is typically reflected in LOTRM through sterilization activities. Unsterilized assets, meanwhile, may appear on the liability side as CIC or other forms of reserve money.

FIGURE 4. CIC creation in the central bank balance sheet

Assets	Liabilities
Net Foreign Assets: +100	CIC: +10 Non-CIC Reserve Money (RM): +10 Liabilities Other than RM: +80

Given the flow of funds from asset accumulation via foreign exchange inflows, and their corresponding liabilities in the form of CIC and LOTRM through sterilization activities, it's not surprising that the correlation between Gross International Reserves (GIR) and CIC and LOTRM is extremely high at 91.6 percent. In terms of growth rates over time, these variables tend to move together as illustrated in Figure 5.

FIGURE 5. Growth rate of GIR and CIC plus LOTRM (January 2003 to August 2024, in percent)



Source: BSP Central Bank Survey (SRF-based), Authors' calculations.

Figure 5 also shows that the pandemic significantly increased domestic liquidity relative to reserve accumulation. While there was a net increase in CIC due to heightened precautionary motives, the surge in domestic liquidity was significantly driven by increasing LOTRM. The spike in CIC and LOTRM on the liabilities side was offset by the increase in domestic claims on the asset side as the BSP extended loans to the national government to help finance its pandemic response.[10]

It's worth noting that this study assumes that the BSP's capital and surplus accounts remain constant over time and are excluded from the analysis as they constitute a small fraction of the BSP's assets. As of July 2024, the BSP's capitalization amounted to PhP60.0 billion. Meanwhile, its accumulated surplus/reserves reached ₱170.9 billion, equivalent to 2.5 percent of the BSP's total assets in the same period.

4. Framework in forecasting CIC: balance sheet approach

The framework starts with the basic accounting identity that assets are equal to liabilities and equity. For simplicity, the equity account is dropped from the identity as it represents a negligible proportion of total BSP assets. Expanding the BSP's assets and liabilities into their respective components, the identity is taken to be:

$$NFA + DC \equiv RM + LOTRM \tag{1}$$

Reserve money could be further broken down into its components, namely: CIC, Liabilities Other than Currency Issued, and Liabilities to Other Sectors:

$$RM \equiv CIC + LODC + LOS \tag{2}$$

Combining equations (1) and (2), the following identity is obtained:

$$NFA + DC \equiv CIC + LODC + LOS + LOTRM \tag{3}$$

Next, isolating CIC in the previous equation yields the following expansion:

$$CIC \equiv (NFA + DC) - (LODC + LOS + LOTRM) \tag{4}$$

The non-CIC liabilities are then grouped under the variable "liabilities other

[10] At the onset of the pandemic, the BSP provided support through a repurchase agreement with the National Government (NG) amounting to ₱300 billion in March 2020, repaid in September 2020. Thereafter, the BSP provided direct provisional advances of no more than 20 percent of the average annual income of the national government and payable within a maximum term of six months. In Bayanihan 2 Act, the BSP can extend additional advances to NG but the amount shall not exceed 10 percent of the average income of NG for the last three years, provided these funds are explicitly earmarked for the government's COVID-19 response programs. The additional amount can only be availed of until 2022 and must be repaid within one year upon availment.

than currency issued" (LOTCI), while the NFA and DC are taken together as "assets":

$$CIC \equiv (Assets) - (Liabilities\ Other\ Than\ Currency\ Issued) \quad (5)$$

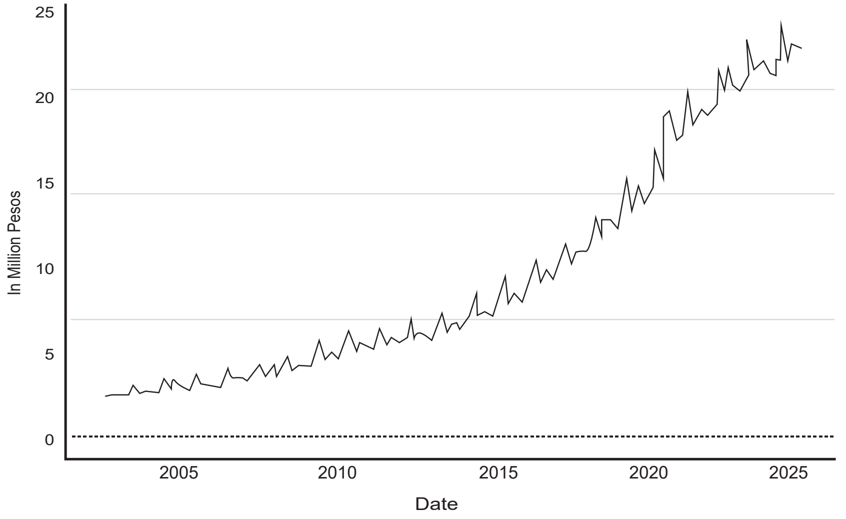
In this framework, CIC is positively related to total assets. To maintain the identity, an increase in assets would require an equal increase in CIC, holding LOTCI constant. On the other hand, CIC is negatively related to LOTCI. An increase in LOTCI should lead to a decrease in CIC, holding assets fixed. This is intuitive as an increase in LOTCI must be offset by a decrease in other components on the liability side to maintain the accounting identity that assets and liabilities are equal.

From Equation (5), we may construct a time series regression model based on historical values of assets and LOTCI to eventually forecast CIC. Likewise, temporal patterns of the stationary series may be modeled as an ARMA process to capture recurrent seasonal dynamics.

5. Data description

The central bank balance sheet data are available monthly, in line with the frequency of reporting of the BSP's balance sheet. The compiled dataset runs from January 2002 to August 2024 for a total of 272 observations. Exploratory analysis reveals some information for the target variable CIC. First, CIC has been trending upwards since 2002 as can be seen in Figure 6, consistent with the growth of the Philippine economy.

FIGURE 6. Currency in circulation (January 2002 to August 2024, in million pesos)



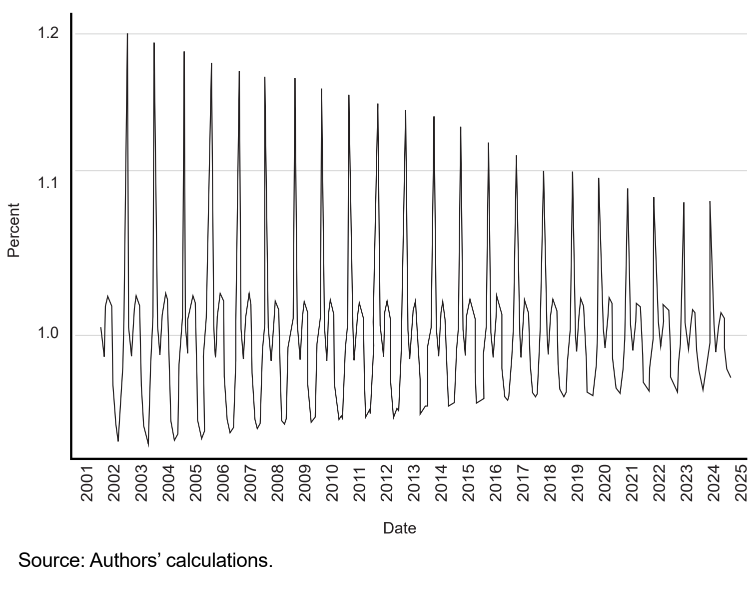
Source: BSP Central Bank Survey (SRF-based), Authors' calculations.

The seasonal index for CIC (Figure 7) reveals consistent peaks every December, reflecting heightened economic activity during the holiday season and the corresponding increase in demand for currency to support transactions. In contrast, troughs are typically observed around July or August, coinciding with the "ghost month," a period marked by subdued financial market activity and lower investment spending. The degree of seasonality appears to be moderating over time, which may point to a gradual smoothing of currency demand. This trend warrants further investigation and could be linked to the growing adoption of digital payments and electronic money platforms.

The *seasonal* package in R was used to perform seasonal decomposition, with the time series frequency set to 12 to reflect monthly data. It employs automated procedures to determine whether transformations (e.g., levels or logs) are needed, detect outliers, and identify trading day and Easter effects. The package also compares competing ARIMA models for signal extraction and selects the best X-13 ARIMA-SEATS specification based on the Akaike Information Criterion (AIC).

For CIC in the Philippines, the automated procedure indicated a preference for log transformation, implying multiplicative seasonal effects, consistent with the pattern observed in Figure 6. A seasonal ARIMA $(0,1,1) \times (0,1,1)_{12}$ model was selected to capture CIC's seasonal behavior, which included significant Easter effects, additive outliers (notably in December 2008, December 2014, and March 2020), and a mean-level shift in March 2020. These disruptions align with the impact of the COVID-19 pandemic and, to a lesser extent, the 2008 Global Financial Crisis on the long-standing seasonal patterns of CIC.

FIGURE 7. Seasonal index of CIC (January 2002 to August 2024, in million pesos)



Source: Authors' calculations.

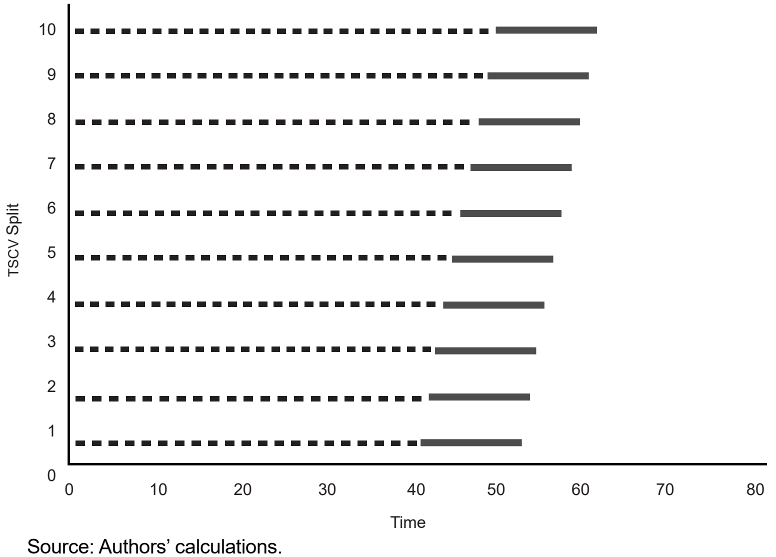
6. Methodology

To achieve stationarity, the first 13 observations were removed after applying both regular and seasonal differencing. The remaining data were then organized into ten sequential training and test sets using the time series cross-validation (TSCV) approach commonly used in machine learning. The first training set includes 239 observations from January 2003 to November 2022, while the corresponding test set covers December 2022 to November 2023. To enable TSCV and ensure sufficient data for estimating seasonal patterns, a sample size of over 200 observations was used. Hence, two decades of data were compiled.

The training and test sets follow a rolling forecast origin, where each training set advances by one period to reflect the monthly release of new data. The final training set spans January 2003 to August 2023, with its corresponding test set covering September 2023 to August 2024. This rolling approach allows the model to be refitted with additional information before generating forecasts. Each test set contains 12 observations, aligning with the practice of forecasting currency-in-circulation (CIC) one year ahead, an approach commonly used by the BSP for planning its currency orders.

TSCV is used to evaluate the forecasting performance of models on "unseen data" and is repeated ten times to ensure consistency in results. A model might perform well on a single test set by chance but fail to generalize across others due to issues like overfitting, shifts in the time series (e.g. changes in the mean level, trend direction or strength, seasonality), or the presence of outliers. Using 10 test sets helps mitigate these risks and provides a more reliable assessment of the model's predictive accuracy. Time series cross-validation can be visualized in Figure 8.

FIGURE 8. Time series cross-validation visualization



Source: Authors' calculations.

As new data becomes available, the training set is extended by one period, allowing the model to be re-estimated with updated information for more accurate predictions. The following 12 observations serve as the test set, reflecting a one-year-ahead forecast horizon in line with the BSP's currency forecasting practices. Rather than focusing solely on the twelfth-step forecast, all 12 predictions in each test set are evaluated to detect any potential decline in predictive performance. The final split represents the most up-to-date model, as it draws on the complete dataset available.

Using the balance-sheet approach in estimating CIC, two time series regression models were estimated: (i) a contemporaneous regression model with ARMA errors, and (ii) a distributed lag model[11] with ARMA errors. Modeling the errors with an ARMA structure would account for serial correlation since the data exhibit patterns over time.

For the ARMA-based models, the variables were transformed to achieve stationarity prior to modeling. In particular, a combination of logarithmic transformation, regular differencing, and seasonal differencing were applied to each variable. In backshift notation, for every variable Y_t, we obtain its weakly stationary form $\tilde{Y}_t = (1 - B)(1 - B^{12})\ lnY_t$. Henceforth, the tilde notation for each variable is used to denote the transformed stationary series. The Augmented Dickey-Fuller (ADF) test and inspection of the autocorrelation function (ACF) plots served as the criteria for stationarity. Model diagnostics are shown in the Appendix.

The proposed models that incorporate balance sheet variables are compared to baseline models, namely Error-Trend-Seasonality (ETS) models and a "pure ARIMA" model. ETS and ARIMA were taken to be baseline models as they rely solely on historical patterns, which according to the literature are preferred in short-term forecasting of CIC. Said models don't assume any theoretical framework in projecting the amount of currency circulating in the economy, hence, do not include any independent variables in the forecasting model.

A demand-for-cash model is not estimated as the BSP relies on GDP in predicting CIC, thereby generating quarterly forecasts. The literature is also unanimous in utilizing GDP as the proxy for the transaction motives to hold cash, ruling out other proxies for transaction motives. The prospect of merging monthly balance-sheet variables with other quarterly and monthly demand-for-cash variables via mixed-frequency models remains an open area of study. Some recommendations and future directions are discussed in Section 8.

6.1. Baseline models

The ETS model is specified below where Y_t is the level of the variable at time t, ℓ_t is the level of the series, b_t is the trend of the series, s_t is the seasonality of the

[11] This is a time series regression model where the covariates are lagged. This model is only used for prediction, while an ARDL model may traditionally be used for policy analysis to capture short and long-term dynamics via cointegration testing (i.e. ARDL bounds testing).

series, and $\hat{Y}_{t+h|t}$ is the point forecast for some horizon h conditional on information at time t [Hyndman and Athanosopolous 2021]. Note that a multiplicative error, additive damped trend, and multiplicative seasonality specification (M-Ad-M) was selected for ETS based on minimization of the corrected Akaike Information Criterion (AICc) in the training sets. The *forecast* package in R was utilized to estimate the ETS models.

In brief, an ETS model is a state-space specification of classical exponential smoothing. The advantage of ETS over classical exponential smoothing is its ability to arrive at forecast distributions aside from point forecasts. It estimates the individual time series components (i.e. level, trend, and seasonality) before aggregating them to form the time series. As for predictions h-steps ahead, the level of the series and the accumulated trend are added together before being multiplied with the estimated seasonal component. A damped trend was selected by the procedure, suggesting a gradual tapering off of the trend over time. The model is summarized below:

$$\begin{aligned} Y_t &= (\ell_{t-1} + \phi b_{t-1})\, s_{t-m}\, (1 + \epsilon_t) \\ \ell_t &= (\ell_{t-1} + \phi b_{t-1})(1 + \alpha\epsilon_t) \\ b_t &= \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\, \epsilon_t \\ s_t &= s_{t-m}\,(1 + \gamma\epsilon_t) \end{aligned} \tag{6}$$

and the predictions are taken to be:

$$\hat{Y}_{t+h|t} = (\, \ell_t + \sum_{j=1}^{h} \phi^j b_t)\, s_{t+h-m[h/m]}$$

where $\epsilon_t = \dfrac{Y_t - \hat{Y}_{t|t-1}}{\hat{Y}_{t|t-1}} \sim N(0, \sigma^2)$ are independent relative errors;

ϕ is the damping parameter to account for changes in the trend;

ℓ_t is the level of the series;

b_t is the slope (or trend) over time;

s_t is the seasonal component;

α, β, and γ are smoothing parameters;

m denotes the number of seasons in a year; and

$[h/m]$ is the is the ceiling function denoting the number of complete seasons spanned by the horizon h.

For the ARIMA-based models, the Box-Jenkins modeling approach was utilized. All variables were taken to be stationary prior to modeling following a logarithmic transformation, along with a seasonal and regular difference to handle regular and seasonal unit roots. Identification of candidate ARIMA models were based on the sample ACF and PACF plots of the residuals. Parameter estimation was conducted through the *forecast* package in R, which uses Maximum Likelihood Estimation (MLE) with Gaussian errors. With sufficiently large sample sizes, the Gaussian maximum likelihood estimator for causal and invertible ARMA models is consistent and asymptotically normal [Yao and Brockwell 2006].

Once autocorrelations were accounted for with the inclusion of ARMA terms, as validated by the ACF and PACF plots, a formal Ljung-Box test was conducted to confirm that residuals were white noise. Finally, model diagnostics, goodness-of-fit statistics and forecast evaluation metrics were inspected to compare the proposed models with the baseline models.

The baseline ARIMA model has a $(0,1,1) \times (1,1,0)_{12}$ specification. Note again that for every variable Y_t, we take its covariance stationary form $\tilde{Y}_t = (1\text{-}B)(1\text{-}B^{12}) lnY_t$. Equation 7 shows the full model in standard multiplicative SARIMA notation.[12] As with ETS, the forecast package in R was used to estimate the time series regression models with SARMA errors. A SAR(1) and MA(1) model[13] parsimoniously capture autocorrelations in the data:

$$\widetilde{CIC}_t = \alpha^{(1)} + u_t^{(1)} \tag{7}$$

$$(1 - \phi_t^{(1)} B^{12})\, u_t^{(b)} = (1 + \theta^{(1)} B)\, \varepsilon_t^{(1)}$$

$$\text{where } \varepsilon_t^{(1)} \sim WN(0, \sigma_{(1)}^2)$$

Errors are modeled as a SARMA process to account for temporal dependencies. Seasonality comes into play as the log-transformed CIC is differenced twice, one regular difference and another seasonal difference, while a SAR(1) term is added to capture seasonal patterns. This baseline model relies purely on the historical behavior of the series to forecast future values of CIC.

For diagnostics, variable stationarity was assessed using the Augmented Dickey-Fuller (ADF) test. Residual checks were also conducted to assess autocorrelation and conditional heteroskedasticity, including the Ljung-Box test, inspection of the ACF and PACF plots, and the ARCH test. These diagnostics help ensure the reliability of parameter estimates in line with the Box-Jenkins modeling framework. A complete set of model diagnostics, covering stationarity, serial correlation, and AR/MA root stability, is provided in the Appendix.

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[12] Superscript (1) and subscript (1) denote the parameters for the baseline model.

[13] If the input data are seasonal with period 12 (i.e. monthly data), this is technically equivalent to an ARMA(12,1) process where the autoregressive parameters are fixed to zero for the first 11 lags.

6.2. Proposed models

ARIMA Model 1 is taken to be a time series model with contemporaneous regressors following an ARIMA $(0,1,1) \times (1,1,0)_{12}$ specification:[14]

$$CIC_t = \alpha^{(1)} + \beta_t^{(2)} \widetilde{Assets}_t + \beta_2^{(2)} \widetilde{LOTCI}_t + u_t^{(2)}$$

$$(1 - \phi_t^{(2)} B^{12})\, u_t^{(2)} = (1 + \theta^{(2)} B)\, \varepsilon_t^{(2)} \tag{8}$$

$$\text{where } \varepsilon_t^{(2)} \sim WN(0, \sigma_{(2)}^2)$$

The errors are modeled as a SARMA process to account for autocorrelation. Said model includes the stationary-transformed central bank assets and LOTCI as independent variables. To arrive at estimates out-of-sample (test set), the transformed regressors were also forecasted with ARIMA so that CIC forecasts 12 months ahead may be generated.[15] This is crucial as for some forecast horizon h, the values of regressors must be available. One potential advantage of this model is that it uses contemporaneous regressors in fitting the model instead of lagged predictors. The more recent information may more accurately capture seasonal dynamics and autocorrelations. The downside is that the regressors also need to be forecasted, potentially compounding forecast errors in predicting CIC out-of-sample. The models for the regressors are as follows:

$$\widetilde{Assets}_t = \alpha^{(a)} + u_t^{(a)}$$

$$(1 - \phi_t^{(a)} B^{12})\, u_t^{(a)} = (1 + \theta^{(a)} B)\, \varepsilon_t^{(a)} \tag{9}$$

$$\text{where } \varepsilon_t^{(a)} \sim WN(0, \sigma_{(a)}^2)$$

$$\widetilde{LOTCI}_t = \alpha^{(b)} + u_t^{(b)}$$

$$(1 - \phi_t^{(b)} B^{12})\, u_t^{(b)} = (1 + \theta^{(b)} B)\, \varepsilon_t^{(b)} \tag{10}$$

$$\text{where } \varepsilon_t^{(b)} \sim WN(0, \sigma_{(b)}^2)$$

The second model adopts a different approach in specifying the exogenous regressors. Lagged values of assets and LOTCI were taken to be the predictors of CIC. In this specification, it is not necessary to add multiple lags to the exogenous regressors since the errors already admit a SAR(1) and MA(1) term to adequately account for serial correlation. The full specification of this dynamic regression model is as follows:

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[14] Superscript (2) and subscript (2) denote the parameters for the first proposed model. The same goes for (3) for the second proposed model.

[15] Superscript (a) and subscript (a) denote the parameters in predicting the Assets regressor. The same goes for (b) in relation to predicting the LOTCI covariate.

$$\widetilde{CIC}_t = \alpha^{(3)} + \beta_t^{(3)} \widetilde{Assets}_{t\text{-}12} + \beta_2^{(3)} \widetilde{LOTCI}_{t\text{-}12} + u_t^{(3)}$$

$$(1 - \phi_1^{(3)} B^{12})\, u_t^{(3)} = (1 + \theta^{(3)} B)\, \varepsilon_t^{(3)} \tag{11}$$

$$\text{where } \varepsilon_t^{(3)} \sim WN(0, \sigma^2_{(3)})$$

In summary, the ARIMA-based models address autocorrelation by specifying the error term using a SARMA structure. These models also incorporate historical information through exogenous regressors, either in contemporaneous or lagged form. The SARMA specification was supported by residual ACF and PACF plots and was chosen to ensure robustness across different scenarios and test sets, avoiding overfitting associated with more complex models that may yield poor forecasts.

As Nau [2020] notes, including multiple AR and MA terms in the same model can lead to the cancellation of roots on both sides of the equation, resulting in unnecessary complexity. AR models are generally more interpretable, as they rely on the variable's own past values rather than unobserved shocks, which are typical of MA models.

From an estimation perspective, MA models involve non-linear parameters and typically require non-linear least squares and numerical optimization, which can result in unstable estimates or convergence issues, especially in models with many MA terms. In contrast, AR models are linear in their parameters and can be estimated using simpler techniques [Diebold 2007]. For these reasons, a parsimonious SARMA model was preferred, balancing model fit, predictive accuracy, and adherence to ARIMA Box-Jenkins assumptions.

6.3. Model selection and forecast evaluation

To assess the performance of both baseline and proposed models, metrics from the training and test sets were compared. Training set performance reflects how well a model fits the observed data, but strong in-sample performance does not always translate to accurate out-of-sample forecasts. A model may still underperform on test data due to issues such as overfitting, structural changes in the variables, or unforeseen shocks not captured in the training set. To evaluate predictive accuracy, forecasts were generated up to twelve months ahead using unseen test data. This was repeated across ten different train-test splits, following the TSCV approach, to provide a more comprehensive view of model performance across various in-sample and out-of-sample scenarios.

For training set performance, the log-likelihood and AIC were compared among the competing models. The AIC is obtained with the expression $2k - 2ln(\hat{L})$ where k is the number of parameters in the model and $ln(\hat{L})$ is the maximized value of the model's log-likelihood function. It is a relative measure of goodness-of-fit as it balances model parsimony (number of parameters) and model fit (log-likelihood). The lower the AIC of a model, the better its fit relative to competing models. Meanwhile, the interpretation of the maximized log-likelihood is straightforward, and a higher value means improved model fit. Both the AIC and log-likelihood are standard goodness-of-fit metrics for MLE-based models.

For both train and test sets, the root mean squared scaled error (RMSSE) was computed. The RMSSE compares model forecasts with a naïve forecast. In this case, the models were compared to a seasonal naïve forecast. In a seasonal naïve forecast, the observation in the same month of the previous year is taken to be the prediction for the current period, i.e., $\hat{Y}_t = Y_{t-12}$. An RMSSE of less than one means that the forecast model is more accurate than the naïve forecast, while a zero RMSSE suggests perfect predictive ability. Formally, the RMSSE is taken to be:

$$RMSE = \sqrt{\frac{1/h \, \Sigma_{t=1}^{h} (Y_{t+h} - \hat{Y}_{t+h})^2}{1/T{-}s \, \Sigma_{t=s+1}^{T} (Y_{t+h} - \hat{Y}_{t-s})^2}} \tag{12}$$

Both RMSSE and AIC are relative measures of error. The advantage of RMSSE is that comparisons are done relative to a benchmark, although there is no direct interpretation. This complements the Mean Absolute Percentage Error (MAPE) metric, which shows forecast errors as a percentage of the actual level of a variable. The interpretation of MAPE is straightforward as a value of 0 suggests perfect predictive ability, and a large MAPE suggests larger errors as a proportion of the target variable.

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100 \tag{13}$$

7. Results and discussion

For the proposed models, the estimated coefficients for assets and LOTCI align with theoretical expectations derived from the central bank's balance sheet identity. Specifically, assets exhibit a positive relationship with CIC, while LOTCI shows a negative relationship, with both coefficients statistically significant at the 1 percent level. Additionally, the SAR(1) term is significant, and the MA(1) component is included to account for serial correlation. Table 1 presents the regression results using the full dataset for the ARIMA-based models.

TABLE 1. Regression output for ARIMA-based models (full data set)

Variable	ARIMA (baseline)	ARIMA Model 1 (contemporaneous)	ARIMA Model 2 (lagged)
Dependent Variable: Currency-in-Circulation (stationary-transformed)			
SAR(1)	-0.44*** (0.06)	-0.28*** (0.06)	-0.28*** (0.06)
MA(1)	-0.05 (0.07)	-0.08 (0.07)	-0.10 (0.07)
Assets		2.52*** (0.10)	2.56*** (0.10)
LOTCI		-1.81*** (0.07)	-1.85*** (0.07)
Number of Observations	259	259	247
AIC	-1,275.68	-1,604.70	-1,530.3
Log-Likelihood	640.84	807.35	770.15

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Figures in parentheses are the estimated standard errors of the regression coefficients

The performance metrics are summarized in Table 2, showing the average results across all ten TSCV splits. ARIMA Model 1 consistently outperforms the other models in terms of both goodness-of-fit and predictive accuracy for both training and test sets. Its AIC is markedly lower, and its training set MAPE is roughly half that of the competing models. The log-likelihood rankings closely follow those of the AIC. Moreover, ARIMA Model 1 has a significantly lower RMSSE, approaching zero, which indicates stronger performance relative to the seasonal naïve benchmark. Collectively, these results point to ARIMA Model 1 as having the best overall model fit.

These results extend to the test sets, where ARIMA Model 1 continues to outperform the other models based on MAPE and RMSSE, metrics used to evaluate predictive accuracy. In ARIMA Model 1, the exogenous regressors (assets and LOTCI) were forecasted using separate ARIMA models, allowing values to be generated for future periods $t + h$. Since these variables can be reliably projected within reasonable bounds, ARIMA Model 1 delivered better predictive performance than ARIMA Model 2, which instead relied on lagged values of the predictors.

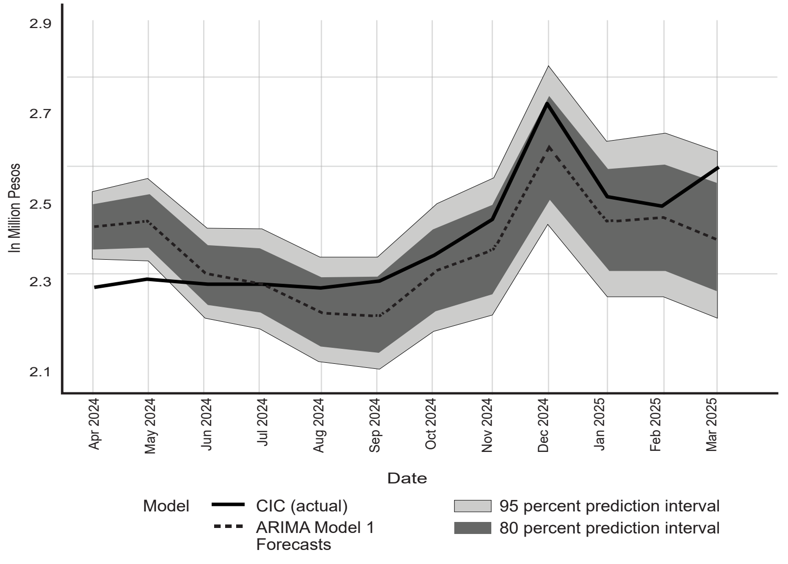
To show how ARIMA Model 1 might perform moving forward, we take the last 12 CIC observations as of writing to be the test set, augmenting the original data set used for TSCV. Model 1 is re-estimated with data points from January 2002 to March 2024, with the test set going from April 2024 to March 2025. Figure 9 shows the path of CIC, along with the forecasts from the preferred model, and its corresponding 95 percent and 80 percent prediction intervals. As expected, the prediction intervals successfully cover most of the actual CIC values in the test set. This indicates strong predictive accuracy.

TABLE 2. Model performance metrics (average in all splits)

	ETS (baseline)	ARIMA (baseline)	ARIMA Model 1 (contemporaneous)	ARIMA Model 2 (lagged)
Dependent Variable: Currency-in-Circulation (stationary-transformed)				
Train Sets:				
Log-Likelihood	-3,120.92	598.42	762.10	574.81
AIC	6,277.83	-1,185.10	-1,507.43	-1,134.07
MAPE	1.46	1.46	0.76	1.44
RMSSE	0.19	0.20	0.08	0.19
Test Sets:				
MAPE	2.75	1.66	1.56	1.80
RMSSE	0.73	0.46	0.45	0.50

Performance gradually decays over time as forecasting over a longer time horizon may lead to compounding forecast errors. In the first six months, the MAPE of ARIMA Model 1 averaged 1.90 percent, before climbing to 4.80 percent in the last six months when the model consistently underestimated CIC. On average, its MAPE is 3.33 percent for all 12 months.

FIGURE 9. Actual CIC vs Model 1 forecasts (April 2024 to March 2025, in million pesos)



Source: Authors' calculations.

8. Ways forward

The balance sheet approach in estimating CIC is useful in generating monthly forecasts as they do not rely on GDP figures that are released quarterly. It is also novel as it does not use demand-side factors anchored on the motives to hold physical currency. While the balance sheet-based models are not intended to replace demand-side models, the proposed models may generate more timely and accurate CIC forecasts for central banks. Improving the prediction of CIC could enhance currency management by aligning currency production more closely with market demand, and enabling more responsive monetary policy. Alternative modeling approaches are particularly valuable during periods of crisis when traditional patterns in the demand for cash break down. This is because demand-for-cash models are typically anchored on GDP, whose relationship with CIC may not hold during economic disruptions.

Future research on CIC modeling could explore alternative techniques such as deep learning models for sequential data, including Long Short-Term Memory networks. Non-linear and long-memory models may also be appropriate, especially for higher-frequency forecasting, referring to what Khatat [2018] calls "second-generation models for currency demand." One promising strategy involves forecasting balance sheet variables using machine learning methods and using those forecasts as inputs to a contemporaneous ARIMA model, preserving interpretability. This mirrors the approach proposed by Prayoga, Suhartono, and Rahayu [2017].

Further investigation into multiple-equation time series models such as Structural Vector Autoregressive Models and State-Space Models, as well as mixed-frequency approaches like Mixed Data Sampling, Dynamic Factor Models, and mixed-frequency VARs, is recommended. These frameworks could provide a means of integrating the demand-for-cash perspective with the balance sheet approach, preserving the role of macroeconomic indicators like GDP while also capturing higher-frequency dynamics present in the central bank's balance sheet.

This study highlights the potential of using the balance sheet as a reliable foundation for forecasting CIC, particularly by leveraging the currency creation process associated with "unsterilized assets" when the BSP accumulates foreign reserves. A logical next step is to expand the set of predictors to include both macroeconomic and currency-specific indicators, an approach already being adopted by other central banks, including the Bank of England [Miller 2017].

With the presence of multiple competing models, forecast averaging or model ensembling could be explored to determine whether combining forecasts leads to more accurate predictions than relying on individual models. Such combinations may produce forecasts that are more resilient to outliers and economic shocks. Since a single model might perform well on one test set but poorly on another, combining forecasts can help leverage the strengths of each model. This approach is particularly relevant here, as the proposed models show consistent accuracy up to six months ahead, with errors increasing beyond that point. Incorporating forecasts from other models that perform better at longer horizons could help improve forecast accuracy.

The proposed models in this paper may be operationalized with other algorithms such as the Hyndman-Khandakar algorithm [Hyndman 2021] for ARIMA order identification if forecasting at scale is the priority. This paper follows the Box-Jenkins algorithm with a stricter criterion that model residuals must follow a white noise process. Likewise, the inclusion of country-specific banking or currency management variables may augment the information provided by the balance sheet.

Acknowledgments: This is an updated version of *BSP Working Paper Series No*. 2022-01.

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Appendix[16]

TABLE A. Stationarity testing of time series variables

	Test Lag Order	ADF Test Statistic	*p*-value
$\widetilde{CIC}_t$	12	-8.18	0.00 (stationary series)
$\widetilde{Assets}_t$	12	-5.19	0.00 (stationary series)
$\widetilde{LOTCI}_t$	12	-5.14	0.00 (stationary series)

FIGURE B1. Correlogram of baseline ARMA model residuals

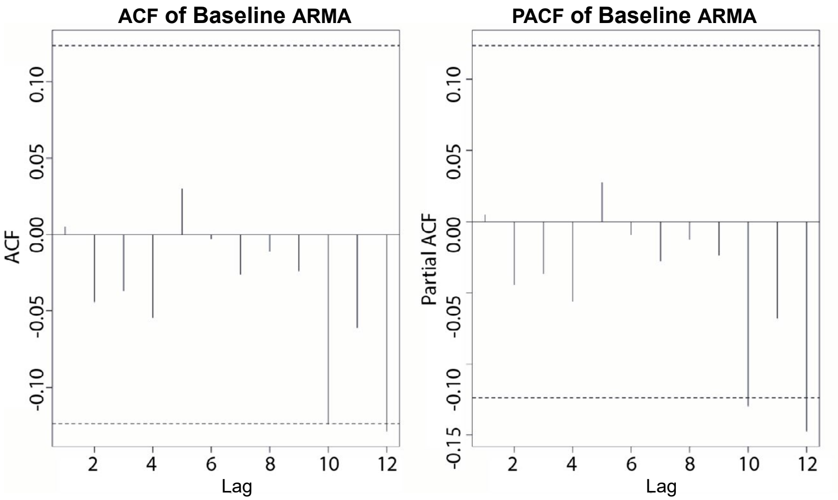
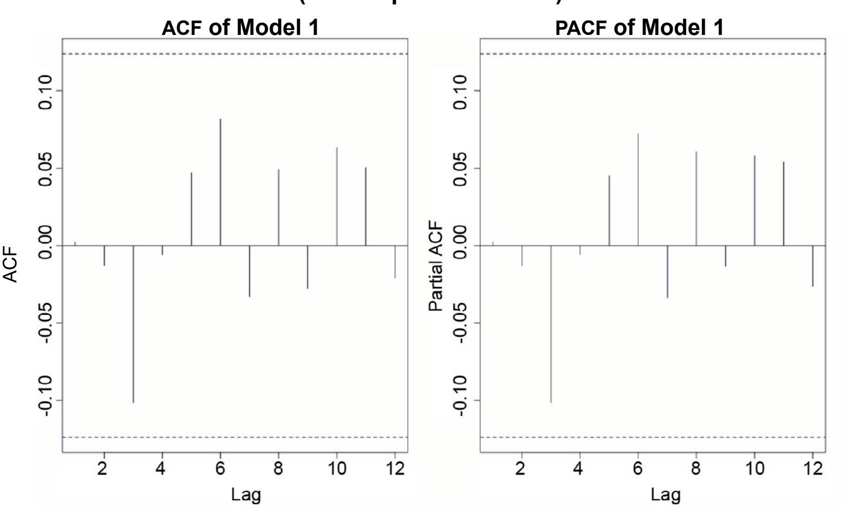


FIGURE B2. Correlogram of proposed Model 1 residuals (contemporaneous X's)



[16] For all statistical hypothesis testing, the type 1 error rate has been set to five percent (i.e., level of significance $\alpha = 0.05$)

FIGURE B3. Correlogram of ARMA model for assets

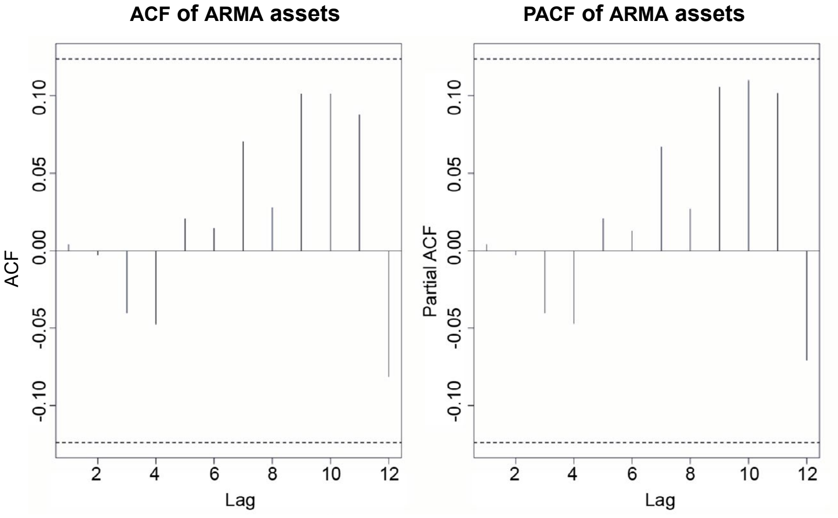


FIGURE B4. Correlogram of ARMA model for LOTCI

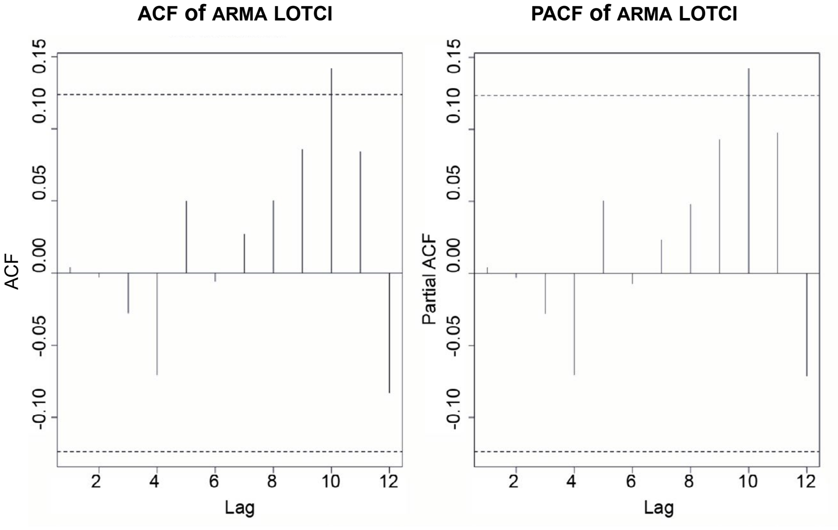


FIGURE B5. Correlogram of Model 2 residuals (lagged X's)

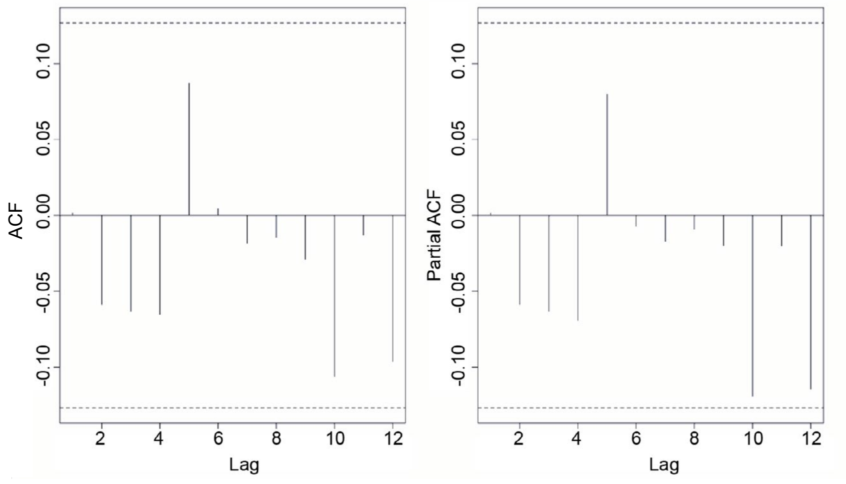


TABLE C. Ljung-box testing of model residuals

	Test lag and DF of test	Ljung-Box test statistic	*p*-value
Baseline ARMA	12	11.64	0.47 (white noise)
Model 1 (contemporaneous *X*'s)	12	7.95	0.79 (white noise)
Assets ARMA	12	11.81	0.46 (white noise)
LOTCI ARMA	12	13.91	0.31 (white noise)
Model 2 (lagged *X*'s)	12	10.33	0.59 (white noise)

FIGURE D1. Inverse AR/MA roots of the baseline ARMA model

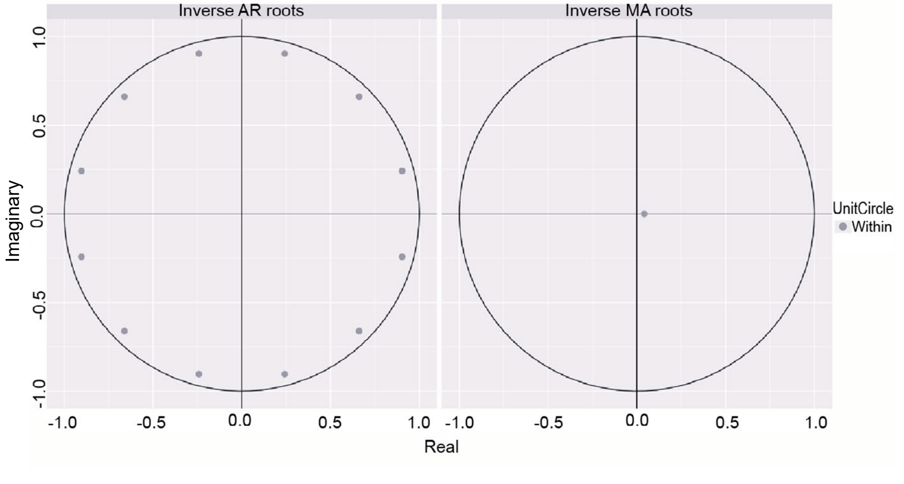


FIGURE D2. Inverse AR/MA roots of Model 1 (contemporaneous X's)

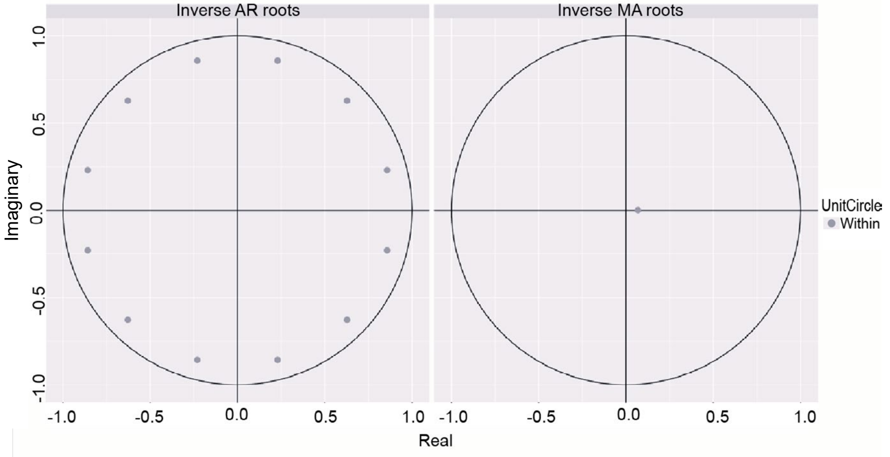


FIGURE D3. Inverse AR/MA roots of ARMA model for assets

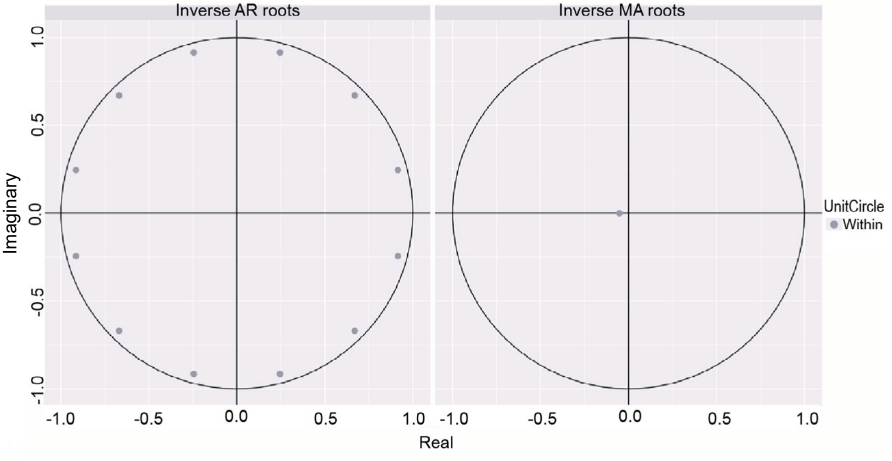


FIGURE D4. Inverse AR/MA roots of ARMA model for LOTCI

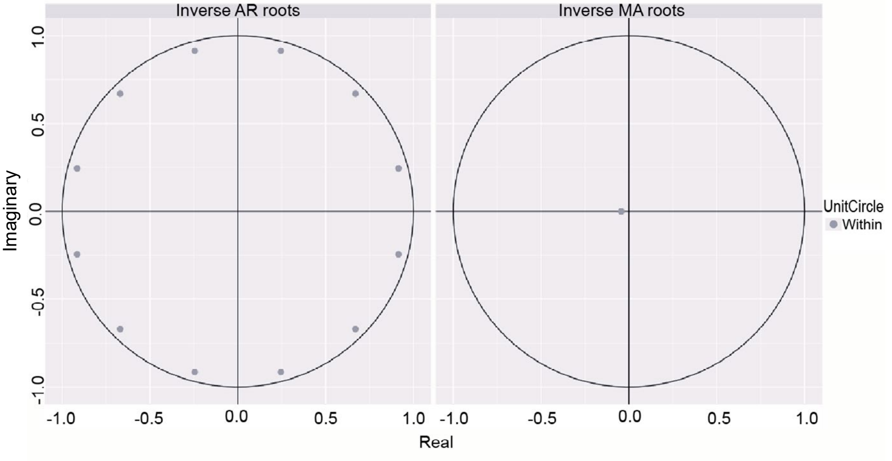


FIGURE D5. Inverse AR/MA roots of ARMA model for assets

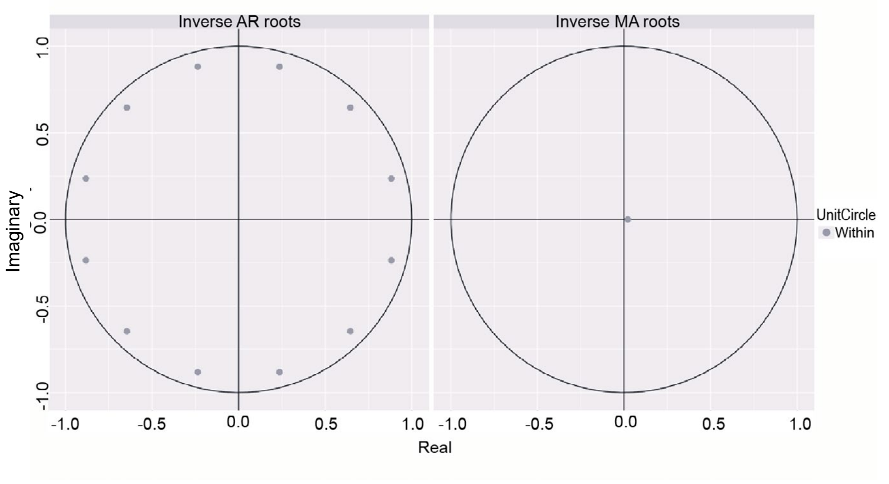


TABLE E. ARCH Lagrange multiplier test

	Test lag order	ARCH LM test statistic	*p*-value
Baseline ARMA	12	64.52	0.00 (ARCH effects))
Proposed Model 1 (contemporaneous *X*'s)	12	27.39	0.01 (ARCH effects)
Assets ARMA	12	12.59	0.40 (no ARCH effects)
LOTCI ARMA	12	11.36	0.50 (no ARCH effects)
Proposed Model 1 (lagged *X*'s)	12	45.61	0.00 (ARCH effects)

PRE The Philippine Review of Economics
62(1):56-76. DOI:10.37907/3ERP5202J

Impacts of access to electricity on employment and household income growth in Cambodia

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This study examines the impacts of access to electricity on household welfare in terms of employment and income growth in Cambodia. To correct for the endogeneity of electricity, we introduce two instruments: (1) population density at village level; and (2) distance between the center of the village and the nearest electricity substation point. Results show a strong and positive effect of household access to electricity on the probability of participation in wage employment and self-employment in the nonfarm sector. Access to electricity contributes to total household income growth through the growth of household nonfarm income. Evidence shows that electrification has facilitated the shift of household livelihood away from self-employment on farms and to wage work in the nonfarm sector, which eventually served as the main driver of household income growth.

JEL classification: J21, O13, Q4
Keywords: access to electricity, employment, household income, Cambodia

1. Introduction

For the achievement of 17 Sustainable Development Goals (SDGs), access to modern energy such as electricity is one of the most essential and fundamental inputs to socio-economic development. Access to electricity is crucial for the provision of basic needs such as food, health, water, education, and transportation. Electricity is an important input for income generation and productive activities particularly in industry and services.

However, it is estimated that 1.2 billion people, 16 percent of the global population, still had no access to electricity in 2014 [International Energy Agency 2016]. In particular, some countries in Asia and the Pacific are struggling to ensure affordable, reliable, and sustainable energy resources to meet their increasing

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energy demands. Like other developing countries in Southeast Asia, Cambodia recognizes that one of the key obstacles to its economic development is the inadequate supply of electricity and basic infrastructure, along with roads and water. As stipulated in Cambodia's socio-economic policy agenda, the national development strategy of Cambodia identifies electricity as one of the priority areas for investment to promote economic and social development.

Except for a few studies such as Saing [2017], Han et al. [2020] and Chhay and Yamazaki [2020], previous studies on Cambodia tend to investigate linkages between various infrastructure and household welfare qualitatively without addressing the endogeneity problem [Bliss 2007; World Bank 2006, 2013]. To reduce concerns about the endogeneity of access to electricity, we employ the instrumental variable (IV) approach with fixed effects and introduce a new instrument, the distance between the center of the village and the nearest electricity substation point. This instrument is an improvement upon previous IVs because we use information on the location of substation points, the first attempt in Cambodia because these data are difficult to obtain. In addition, we shed light on how electrification benefits household welfare in both urban and rural areas, while most of the existing studies focus on only rural areas.

Using nationally representative household survey data, the estimation results show a strong and positive effect of household electrification on wage employment and self-employment in the nonfarm sector. With regard to household income, our findings indicate that increased access to electricity contributes to total household income growth through an increase in nonfarm income. Furthermore, the effect of electrification on income growth is much stronger in urban areas. These results suggest that electricity projects, by creating jobs and stimulating the development of the nonfarm sector, could serve as an effective instrument in improving household welfare. The rest of this paper is organized as follows: Section 2 provides the literature review and testable hypotheses. Section 3 describes the datasets and the changes in the sources of income with the expansion of electricity coverage. Section 4 describes the estimation strategy, while Section 5 presents the estimation results and Section 6 checks for robustness. Finally, Section 7 concludes this paper.

2. Literature review and testable hypotheses

Many previous studies have investigated the effects of electrification on household welfare in developing countries, but the results on employment structure have been mixed. For example, some studies observed positive impacts of electrification on female employment, while there is no statistically significant impact on male employment (Dinkelman [2011]; Grogan and Sadanand [2013]; Dasso and Fernandez [2015]). Rathi and Vermaak [2018] found that access to electricity in India increases paid employment for women while it decreases paid employment for men. They explained that access to modern technology via electricity frees up women's time from household chores, allowing them to engage in income-generating activities. On the contrary, men may drop out of the labor force as a result of extra income from female family members. However, Vande Walle et al. [2015] found a positive impact on both male and female labor supply in India. For men, the results indicate a significant substitution in labor supply from casual to regular work since electricity allows longer working times including night time. For women, the main effect is to increase casual wage work, while no evidence of wage increase was found. Furthermore, Lipscomb et al. [2013] estimated the development effects of electrification across Brazil and found large, positive effects of electrification on employment in both formal and informal sectors. Chhay and Yamazaki [2020] and Fetter and Usmani [2020] assessed the impact of electrification in rural Cambodia and India respectively and found that access to electricity significantly increased non-agricultural employment. To sum up, results from the existing literature are mixed on the impacts of electricity on employment.

Given the aforementioned, we propose the following hypotheses relating electricity to employment:

Hypothesis 1 (H1): Access to electricity increases the probability that household members are engaged in wage employment in nonfarm sectors.

Hypothesis 2 (H2): Access to electricity induces household members to start their own household businesses in the nonfarm sector.

With regard to household income, some studies found significant positive impacts, especially on nonfarm income, but the effects on agricultural income are small or not significant (Kumar and Rauniyar [2018]; Charkravotry et al., [2014]; Khandker et al., [2014], while other studies failed to observe any effects [Peters and Sievert 2016].

Based on the above observations, we postulate the following hypotheses on electricity and household income growth:

Hypothesis 3 (H3): Access to electricity contributes to total household income growth through increased household nonfarm income.

Hypothesis 4 (H4): Access to electricity does not significantly affect agricultural income.

3. Data set and household sources of income

3.1. Dataset

This study mainly uses Cambodia Socio-Economic Survey (CSES) data for 2004, 2009, 2014, and 2017. These are nationally representative household survey datasets collected by the National Institute of Statistics under the auspices of the Ministry of Planning of the Royal Government of Cambodia. The main objective of the survey is to collect statistical information about the living conditions of the Cambodian population and the extent of poverty. CSES contains information related to income and welfare indicators such as health, education, housing conditions, economic activities, and access to infrastructure including electricity, roads and piped water.

We used CSES data for 2004, 2009, 2014, and 2017 for descriptive analyses. For the regression analysis, we selected 2004, 2009 and 2014 because these surveys have a large sample set, which is done every five years since 2004. We limit the individual sample to those of working age (15 to 58 years old). The total sample size is 12,307 households (43,027 individuals) in 2004; 10,209 households (35,319 individuals) in 2009; 15,218 households (53,022 individuals) in 2014; and 3,840 households, (16,909 individuals) in 2017. The CSES has several advantages. First, the datasets are nationally representative, covering all 24 provinces of Cambodia. Second, the data include comprehensive information on household income sources along with descriptions of occupation and industry, employment status (employee, employer, own account worker and unpaid family worker), and wages of paid employees among household members. Furthermore, the data include all sources of household income, such as income from agriculture; income from nonfarm economic activities; and income from other sources such as remittances and pensions. This enables the calculation of total household income from all income sources. Finally, the survey includes questionnaires related to infrastructure including sources of lightning at both household and village levels.

In addition to the CSES data, the Economic Census of Cambodia (ECC), which covers all establishments in Cambodia, is used for descriptive analysis to better capture a comprehensive picture of how electrification has affected employment from the labor demand side. Finally, data from the country's Population Census for 1998 and 2008 were used to construct the population density of the village, which is one of our two instrumental variables, along with the distance between the center of the village and the nearest electricity subpoint.

3.2. Description of sample households

Regarding main sources of lighting, more than half of all households used kerosene lamps, while the percentage of households with access to publicly provided electricity was only 16 percent in 2004. The latter proportion increased significantly from 27 percent in 2009 to 61 percent in 2014 and 82 percent in 2017, thanks to several development assistance projects, which extended coverage of electricity grids. However, these rates are low compared to other CLMV countries (Laos, Myanmar, and Vietnam). This is the result of conflict and civil war under the Pol Pot regime in the 1970s when almost all electricity facilities, including generation, transmission, and distribution facilities, were destroyed throughout the country. Furthermore, there remains a significant urban-rural gap in the percentage of the population with access to electricity.

Regarding the characteristics of households with access to electricity (defined as households using publicly provided electricity/city power as their main source of lighting) and those without electricity, important characteristics for comparison are the educational attainment of household members and their sector of employment and sources of household income. We classify the sector of employment into (1) wage employment, (2) self-employment in the farm sector, (3) self-employment in the nonfarm sector, and (4) unpaid work. Sources of household income are farm, nonfarm, and other income which includes remittances and social benefits among others.

Electrified households have higher levels of schooling attainment and this is particularly noticeable for the proportion of working-age members with tertiary schooling. In contrast, more than 60 percent of members from households without electricity have partially or fully completed primary schooling (1-6 years). A higher proportion of working-age members from households with electricity are engaged in wage work and self-employment in the nonfarm sector, in contrast to members of households with no electricity who are largely engaged in self-employment on farms or work as unpaid workers. Nonetheless, the proportion of unpaid workers in households with no electricity has gone down substantially from 39 percent in 2004 to 23 percent in 2009 to 5 percent in 2014.

Electrified households are better off: they have higher income, especially nonfarm income. The ratio of average monthly income between electrified households and non-electrified households declined from 3.17 in 2004 (USD 476 versus USD 150 in USD PPP in 2010) to 1.87 in 2009 (USD 665 versus USD 354) to 1.46 in 2014 (USD 689 versus USD 469) to 1.49 in 2017 (USD 729 versus USD 490). Non-electrified households have caught up mainly because they have received higher nonfarm income and other income including remittances. Furthermore, electrified households have more assets, such as radio, TV and mobile phones, which may contribute to improving access to information.

At the village level, villages with access to grid electricity have much shorter distances to bus stops, which suggests that transport accessibility is better. The number of functioning large industrial enterprises and infrastructure development projects is higher for villages with access to grid electricity than for those without electricity. However, it is not clear whether these necessarily imply a causal effect of electrification.

3.3. Changing sources of household income

A summary of household income sources in Cambodia is presented in Table 1. We classify income into three major categories: (1) income from wage work, (2) income from self-employment, and (3) other income. Income from wage work comes from agriculture and non-agricultural sectors including manufacturing and services. The manufacturing sector includes garments, food, wood, metal, and others. Income from services includes earnings from construction, retail, government, transport, business services, and other categories. Self-employment income from agriculture comes from crop farming, animal raising, fishing, forestry, and hunting. Self-employment income from services comes from retail, transport, business services, and other sources. Other income consists of domestic and overseas remittances, and others such as pensions, transfers, bank interest, and dividends.

TABLE 1. Monthly household income sources in Cambodia (USD PPP in 2010)

	2004	2009	2014	2017
Wage work	84 (39%)	109 (26%)	265 (41%)	393 (57%)
Agriculture	20 (9%)	33 (8%)	68 (11%)	27 (4%)
Manufacturing[1]	4 (3%)	7 (1%)	21 (2%)	101 (15%)
Service[2]	60 (27%)	69 (15%)	176 (27%)	264 (37%)
Self-employment	119 (55%)	305 (72%)	301 (47%)	263 (39%)
Agriculture	61 (28%)	143 (34%)	91 (14%)	61 (9%)
Manufacturing	4 (2%)	13 (3%)	18 (3%)	13 (2%)
Retail services	39 (18%)	79 (19%)	134 (21%)	132 (19%)
Other services[3]	15 (8%)	70 (16%)	58 (9%)	57 (8%)
Other income	12 (6%)	9 (2%)	74 (11%)	29 (4%)
Remittances	8 (4%)	6 (2%)	53 (9%)	24 (4%)
Others	4 (2%)	3 (0%)	20 (2%)	5 (0%)
Total income	215 (100%)	423 (100%)	640 (100%)	686 (100%)

Note 1-3: "Manufacturing" includes mining, garments, food, wood, metal and others, "Service" includes construction, retail, government, transport, business services, and others.
Source: Authors' calculations from the Cambodia Socio-economic Survey.

The average total monthly household income in Cambodia increased from USD 215 PPP in 2004 to USD 686 in 2017, a more than threefold increase (Table 1). This was mainly because of the increase in income from wage work in the nonfarm sector, most notably in the garment industry as well as in service sectors such as construction, government, and business. There was a shift in household income structure away from self-employment in agriculture to wage work in manufacturing and services. The share of self-employment income from agriculture declined from 28 percent in 2004 to nine percent in 2017. The share of wages in manufacturing increased from three percent to 15 percent while the share of services rose from 27 percent to 37 percent in the same year. Government services (administration of the state, provision of services to the community, and compulsory social security activities) are the main sources of wage income across all years. The decline in self-employment income from agriculture indicates the declining importance of crop farming, animal husbandry and fishing and hunting as a source of livelihood. Wage income from agriculture, which made up nine percent of total household income in 2004, has become much less important, as its share of total household income has declined to four percent.

Interestingly, the share of crop income increased from 11 percent in 2004 to 27 percent in 2009, as a result of the higher value of production of rice after the increase in rice prices and rice production during the Asian food crises in 2007 to 2009. According to the World Bank [2013], the price of rice (in constant value) increased by 37.1 percent from 2004 to 2009, boosting farmer income and providing incentives to increase production. In addition, according to FAOSTAT data, the area used for rice production expanded from 2.1 million hectares in 2004 to 2.7 million in 2009 (27 percent increase) and rice yield increased from an average of two tons per hectare in 2004 to an average of 2.8 tons per hectare in 2009 (43 percent increase).

Self-employment in the nonfarm sector such as manufacturing, retail services and other services remains an important source of income accounting for roughly one-third of the total household income in all years. In particular, income from retail services has consistently remained an important source of income, accounting for nearly 20 percent of total income in all years. As a result of Cambodia's real estate boom, fueled by investment from China, income from the construction sector became the second largest income source in Cambodia's service sector in 2009, followed by income from business services (financial intermediation, renting, and business activities) and transport services (transport, storage, and communication).

In summary, there is a clear shift in household income structure away from agricultural self-employment and to nonfarm wage work. Such a shift has been accompanied by income growth. The shift in household income sources has coincided with the expansion of electricity coverage in the country. Households have been increasingly engaged in electricity-intensive sectors such as garments, construction, government, and business services. Here we inquire whether electricity has a significant impact on the choice of employment and household income.

4. Estimation strategy

To examine the impact of access to electricity on employment and household income growth, we obtain household electrification status data from a household questionnaire within CSES survey data. We define treatment households as those having access to publicly provided electricity or city power (national electricity grid provided by the government) and control households as those which do not have such connection and hence use generator, battery, or kerosene lamp as their main source of lighting.

To identify the causal effects of electrification on employment and household income, we have to control for the endogeneity of project placement. The Cambodia Energy Sector Strategy 2004 specified that the electrification strategy in Cambodia tends to give priority to areas with the best potential for economic development and with higher income levels, which suggests that project placement is not random. Therefore, to resolve the endogeneity problem, this study employs an instrumental variable (IV) estimation with fixed effects. The impact of electrification is identified using the following equations:

$$\hat{E}_{hvt} = \alpha_1 + Z_V + \pi_1 H_{hvt} + V_{vt} + \lambda + \theta_t + \varepsilon_{hvt}, \tag{1}$$

$$Y_{ihvt} = \alpha_2 + \beta_2 \hat{E}_{hvt} + \delta_2 X_{ihvt} + \pi_2 H_{hvt} + V_{vt} + \lambda + \theta_t + \varepsilon_{ihvt}, \tag{2}$$

$$Y_{hvt} = \alpha_3 + \beta_3 \hat{E}_{hvt} + \pi_3 H_{hvt} + V_{vt} + \lambda + \theta_t + \varepsilon_{hvt}. \tag{3}$$

Household's access to electricity is predicted by using instrumental variables (IVs): Z in Equation (1); and then our interest variable, the predicted value of the access to electricity ($\hat{E}_{hvt}$), measured by the coefficient (β), is used in the second stage outcome equations. This is effective since IVs break the correlation between the treatment and the error term, eliminating the endogeneity bias [Khandker et al. 2009].

Regarding the outcome variables, Y_{ihvt} in Equation (2) represents the outcome variables of individual i of household h in village v at time t. We examine four outcomes related to employment at an individual level: (1) a binary variable for an individual i of working age who is a paid employee, generally categorized as wage employment; (2) a binary variable for an individual i of working age who is self-employed in the nonfarm sector; (3) a binary variable for an individual i of working age who is self-employed in the agriculture sector; and (4) a binary variable for an individual i of working age who is an unpaid family worker.

The variable, Y_{hvt} in equation (3) represents household income, (1) log of monthly total household income, (2) log of monthly income in the nonfarm sector (including both wage income and income from self-employment), (3) inverse hyperbolic sine transformation of income in the agriculture sector and (4) log of monthly other income. We use the inverse hyperbolic sine transformation because a substantial number of households in urban areas have no income in agriculture. Regarding control variables, X_{ihvt} is a vector of individual-level characteristics, including gender (1 if female and 0 if otherwise), age, age-squared (to detect non-linear effects of age), a dummy variable for marital status of individual i (1 if married), and years of education. H_{hvt} is a vector of household-level characteristics, including a binary variable indicating whether the household resides in an urban area (1 if urban, 0 otherwise); the number of toddlers aged 0 to 6; the area of irrigated land used for rice and other crop production (in hectares); and household assets (defined as the number of radios, televisions, mobile phones, and personal computers), in the case of equation (2).

In the case of the equation (3), H_{hvt} includes the dummy variable whether a household head is female, the number of household members aged 15 to 20, 21 to 30, 31 to 40, 41 to 50 and 51 to 58 years old, proportion of household members who are female, proportion of household members who completed primary school, secondary school and tertiary school, a binary variable for household living in urban area, and size of irrigated land for production of rice and other crops (hectares). V_{vt} is a vector of village-level characteristics including distance to the nearest bus stop, a binary variable for the presence of large industrial enterprises (e.g., factory, company employing more than 10 persons, hotel or restaurant), a binary variable for the presence of infrastructure development projects (e.g., road development), the proportion of female and male who are employed in the village and mean monthly earnings from wage employment in the village, which may partly reflect the scope of local labor market opportunities. District-level fixed effects are denoted as λ and year-fixed effects are denoted as θ_t. ε_{ihvt} is an error term representing unobserved variables. Finally, standard errors are clustered at the village level.

The IVs we propose are: (1) population density at village level and (2) distance between the center of the village and the nearest electricity substation point. First, in the prediction of household access to electricity, one plausible exogenous factor is population density at the village level before the expansion of electrification projects. If the extension of a given length of grid cable reaches fewer customers in an area where customers are widely dispersed, i.e., areas with low population density, the marginal cost of an additional household connection is relatively high. Thus, population density is a cost-related factor; and is one of the keys to our identification strategy. In this study, we use population census data collected in 1998 and 2008 by the Cambodian Ministry of Planning. The proportion of households with electricity was 13 percent in 1998 and 26 percent in 2008, which is substantially low compared to 82 percent in 2017. Thus, it is reasonable to conclude that the period 1998–2008 is the period before the electrification projects expanded. Population density at the village level during 1998-2008 can be considered exogenous and one of the significant factors influencing the status of village electrification in later periods.

Second, we propose the "distance between the center of the village and the nearest electricity substation" as a second IV to predict electricity availability. In general, there are four steps in the provision of electricity by an electrical network. First, power is produced at the power plant. Second, it is transmitted along transmission lines to substations. Third, at the substation, the voltage is lowered from 230kv to a level that can be distributed to consumers. Finally, power is distributed along distribution lines from substations to households in a connected village. Thus, it is plausible to suggest that a household located in a village near an electricity substation has a higher probability of being connected to the electricity network than one in a village far from any substation. Furthermore, that distance does not affect our outcome variables related to employment and household income. According to the government's announced electricity expansion strategy, the focus is on areas which are far from the substation points, indicating that distance is one of the important elements for targeting electrification areas in Cambodia. Thus, based on the above arguments, the proposed two IVs (population density and household distance to the nearest electricity substation) could sufficiently address the endogeneity issue associated with household access to an electric grid.

5. Results

5.1. First stage results

To examine whether there are any obvious violations of the IV approach, we first test whether or not the IVs are good predictors of the endogenous variable, household access to electricity. Table 2 shows the first stage results of prediction of household access to electricity using the two IVs, (1) population density at the village level in 1998; and (2) distance between the village center and the nearest electricity substation point. The fit is very strong: the coefficients of both IVs are statistically significant at the one percent level. Furthermore, they are also jointly significant with a p-value equal to zero and high F-statistics, indicating that the IVs are strong.

TABLE 2. First stage regression results

Outcome	**Household access to electricity**	
Instruments	**(1)**	**(2)**
1. Population density	0.0185*** (0.0058)	0.0187*** (0.0051)
2. Distance between village and a nearest electricity substation point	-0.0623*** (0.0224)	-0.0533*** (0.0181)
Observations	96,760	26,714
Joint significance of all IVs	F=9.13	F=11.77
Hansen J statistics	3.505 Chi-sq(1) P-val = 0.0612	0.088 (Chi-sq(1) P-val = 0.7663)

Note: Column (1) shows the first stage regression results at individual level with all the control variables. Column (2) shows the first stage regression results at household level with all the control variables. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3. Exclusion restriction

	Employment				Income			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**Wage emp**	**Self-employment in nonfarm sector**	**Self-employment in farm sector**	**Unpaid**	**Total income**	**Nonfarm income**	**Farm income**	**Other income**
ln_population density	0.00169	0.0060657	-0.00655	-0.00510*	-0.0112	0.0330*	-0.0402	0.0178
	(0.00355)	(.0045493)	(0.00660)	(0.00283)	(0.0128)	(0.0182)	(0.0247)	(0.0400)
ln_distance	-0.0502***	0.00593	0.0535**	0.0323***	0.0363	0.0516	0.0884	-0.0334
	(0.0127)	(0.00473)	(0.0214)	(0.0115)	(0.0465)	(0.0580)	(0.0737)	(0.184)
Observations	46,176	46,176	46,176	46,176	13,370	5,622	5,263	3,609
R-squared	0.116	0.098	0.228	0.246	0.309	0.363	0.189	0.356

Note: The dependent variables are (1) whether an individual is employed as a wage earner (paid employee), (2) self-employed in nonfarm sector, (3) self-employed in farm sector, (4) unpaid family worker, (5) log of total monthly household income, (6) log of monthly income in nonfarm sector, (7) log of monthly income in farm sector and (8) log of monthly other income. The sample is limited to observations before the village had electricity. All errors are clustered at village level. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

It is essential to ensure that the IVs are exogenous, namely the IVs should not correlate with the error term of the outcome equations. First, this test can be performed using Hansen's *J* statistic, under the null hypothesis that the over-identification restriction is satisfied; that is, the IVs are not correlated with the error term of the outcome equation. As can be seen in Table 2, the results of Hansen's *J* statistic are insignificant, suggesting that the null hypothesis cannot be rejected, which in turn implies that the over-identification restriction is satisfied. Thus, it is reasonable to say that the proposed IVs do not affect our outcome variables and are not correlated with the error term. The second test is to check the exclusion restriction of the IVs to the outcome variables before the expansion of electricity projects following Squires [2015]. If the IVs satisfy the exclusion restriction, we would expect them to have an impact on the probability that households have access to electricity, but not on the outcome variables before electrification. Table 3 shows that except for a few cases (i.e., the distance between the center of the village and the nearest electricity substation point with respect to employment), the IVs do not significantly impact the outcome variables before electrification.

Overall, these tests suggest that the two IVs (1) population density at the village level; and (2) distance between the center of the village and the nearest electricity substation point have a strong first-stage impact on electrification and that there is no strong evidence that the IVs fail the exclusion restriction.

5.2. Second stage results

5.2.1. Electricity and employment

Since household income sources are affected by the probability of employment of working-age members, we explore the factors affecting individual member employment as related to the impact of electricity. Table 4 shows the results of IV estimations at the individual level with all the control variables at the household and village level, as well as, year and district fixed effects related to employment defined as follows: (1) wage employment, (2) self-employment in the nonfarm sector, (3) self-employment in the farm sector and (4) unpaid family worker. The estimation is performed for women and men separately.

Column (1) of Table 4 shows the two-stage least squares (2SLS) estimation results of the impact of household electrification on the probability of wage employment for all individual samples of working age. As the table shows, our interest variable, the binary variable household access to the electricity grid, is positive and significant, which supports our *H1: Access to electricity increases the probability that household members are engaged in wage employment in nonfarm sectors.* By gender, the value of the coefficient of electricity dummy is greater among men than among women. These results indicate that the effect of household electrification on male time allocation is much larger than that on women because men are usually the main earners of households and spend more time working as employees.

For women, the coefficient of the number of small children aged 0 to 6 years old is negative and significant indicating that household production activities matter a lot for women's decision in wage work.

TABLE 4. Impact of electrification on employment (2SLS estimation results)

		All		
	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	**Wage employment**	**Self-employment in nonfarm sector**	**Self-employment in farm sector**	**Unpaid family worker**
Electricity (1=yes)	0.329**	0.496**	-0.726***	-0.245***
	(0.108)	(0.196)	(0.228)	(0.090)
Observations	96,760	96,760	96,760	97,760
		Women		
Electricity (1=yes)	0.267**	0.375**	-0.649***	-0.231*
	(0.119)	(0.173)	(0.221)	(0.123)
Observations	47,205	47,205	47,205	47,205
		Men		
Electricity (1=yes)	0.453**	0.498**	-0.735**	-0.256***
	(0.148)	(0.200)	(0.243)	(0.084)
Observations	45,788	45,788	45,788	45,788

Note: The dependent variables are (1) whether an individual is engaged in wage employment, (2) self-employment in the nonfarm sector, (3) self-employment in the farm sector, and (4) work as an unpaid family worker. The control variables at individual, household, and village levels are included. District and year fixed effects are included. All errors are clustered at village level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Next, in the case of self-employment in the nonfarm sector, the coefficient of the dummy variable of household access to electricity is positive and significant for all specifications (Column 2). By gender, the coefficient of the dummy variable of household access to electricity is higher for males than for females (37.5 percent for males and 49.8 percent for females), which partly supports our *H2: Access to electricity induces household members to start their own household businesses in the nonfarm sector*.

Self-employment in the farm sector is largely related to rice production, as rice is a major crop in Cambodia. For all specifications, the effect of electrification on the probability of engagement in self-employment in the farm sector is negative and significant (Col 3). Furthermore, no clear gender difference is observed in the effects of electricity on self-employment in the farm sector. Finally, the results of the estimation for unpaid family workers are reported in column (4). The coefficient of the dummy variable of household access to electricity is negative and significant in all the specifications, suggesting household access to electrification contributes to the reduction of unpaid family workers and the effect is greater among males.

In summary, the estimation results show that household access to electricity increases the probability of work in wage employment and self-employment in the nonfarm sector, and decreases the probability of self-employment in the farm sector and unpaid work; all of which indicates that electricity induces working-age individuals in the households to shift their economic activities to more profitable endeavours in the nonfarm sector such as salaried work and self-employment and away from self-employment on farm and unpaid work.

5.2.2. Electricity and household income

Next, we examine the impact of electrification on the log of monthly household income: (1) total household income; (2) nonfarm income; (3) farm income; and (4) other income. The results of the IV estimations with all the control variables at the household and village levels, as well as year and district fixed effects, are reported in Table 5. All estimations are performed in both urban and rural areas.

Column (1) of Table 5 shows the results of the estimation of the impact of electrification on the log of monthly total household income. Estimation result shows household access to electricity has a positive impact on total household income, though it is not significant. The effect of electrification is much stronger in urban areas than in rural areas, where the impact is insignificant since households in rural areas rely more on farm income.

TABLE 5. Impact of electrification on household income (2SLS estimation results)

	All			
	(1)	(2)	(3)	(4)
VARIABLES	Total monthly income	Nonfarm income	Farm income	Other income
Electricity (1=yes)	0.388 (0.369)	1.228** (0.484)	-1.1916*** (0.586)	-0.815 (0.869)
Observations	26,714	15,495	21,534	7,583
	Urban			
Electricity (1=yes)	1.159** (0.475)	1.433* (0.800)	-5.643*** (1.800)	-1.095 (1.297)
Observations	6,117	5,324	6,299	1,593
	Rural			
Electricity (1=yes)	0.0551 (0.393)	1.191*** (0.437)	-4.265*** (1.296)	-0.240 (0.922)
Observations	20,597	10,171	21,324	5,990

Note: The dependent variables are (1) log of total monthly income, (2) log of nonfarm income, (3) Inverse hyperbolic sine of Farm income, and (4) log of other income. The control variables at individual, household, and village levels are included. District and year fixed effects are included. All errors are clustered at village level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

As for nonfarm income (including both income from wage employment and self-employment) (Col 2), the effect of electrification is positive and significant and much stronger compared to that for total income, which supports *H3: Access to electricity contributes to total household income growth through increased household nonfarm income*. Regarding geographic area, the effect of electricity on nonfarm income is positive and significant in both urban and rural areas and is much stronger in urban areas. As for farm income (Col 3), the results of IV estimations show that the impact of electricity is negative and statistically significant at the one percent level, which partially rejects *H4: Access to electricity does not significantly affect agricultural income.* The negative effect is much stronger in rural areas. This could be explained by the fact that electrification makes nonfarm activities more profitable than farming, inducing people to switch out of farming into nonfarm activities as a result of electrification.

Finally, the results of the estimation of other income, which are all non-labor income, are reported in Column (4). Other income includes income from sources such as remittance, pensions, and interest on loans. In particular, remittance (both domestic and abroad) accounts for about 70 percent of other income sources. The result shows that the effect of household access to electricity on other income is negative but insignificant. By region, there is a negative association between access to electricity and other incomes in both urban and rural areas—though none of those associations are significant. Overall, there is no clear evidence that electrification affects non-labor income.

6. Robustness check

Here we examine the sensitivity of our results using two strategies: (1) employing the OLS with village fixed effects using village-level panel data, and (2) investigating the spillover benefits of village electrification on non-electrified households.

6.1. Panel data at village level

To test for sensitivity and to control for time-invariant confounding factors at the village level, we restrict the samples to panel data at the village level. We use the same estimation strategies in Equations (1) and (2) as explained in Section 4 and employ village-fixed effects rather than district-fixed effects. The results of the OLS estimations, which include all control variables at the individual, household, and village levels, as well as year and village fixed effects, related to individual employment, are reported in Table 6.

TABLE 6. Impact of electrification on employment using village-panel data

VARIABLES	(1) Wage employment	(2) Self-employment in nonfarm sector	(3) Self-employment in farm sector	(4) Unpaid family worker
All				
Electricity (1=yes)	0.104***	0.172***	-0.105**	-0.00611
	(0.0380)	(0.0475)	(0.0448)	(0.0239)
Observations	10,567	10,567	10,567	10,567
Women				
Electricity (1=yes)	0.0470	0.171***	-0.154***	-0.00278
	(0.0358)	(0.0512)	(0.0523)	(0.0284)
Observations	5,492	5,492	5,492	5,492
Men				
Electricity (1=yes)	0.140***	0.162***	-0.0553	-0.00499
	(0.0450)	(0.0496)	(0.0543)	(0.0243)
Observations	5,075	5,075	5,075	5,075

Note: The dependent variables are (1) whether an individual is employed as a wage employment, (2) self-employed in nonfarm sector, (3) self-employed in farm sector, and (4) unpaid family worker. The control variables at individual, household, and village levels are included. District and year fixed effects are included. All errors are clustered at village level. Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Overall, the effect of household access to electricity on employment is similar to our main results using data for all villages. There is an increased probability of wage employment with access to electricity, with the effect much stronger for males. Electricity has a positive impact on the probability of self-employment in the nonfarm sector for both women and men, with the effect slightly higher for women reflecting the fact that self-employment activities in the nonfarm sector are performed within the confines of homes, so women can easily combine them with household chores and domestic activities. There is a negative association between access to electricity and self-employment in the farm sector, although the effect is small and insignificant for males. Finally, the effect of electrification is negative but insignificant on the probability of unpaid work, reflecting a weak association between the presence of electricity and unpaid work.

The results for household income shown in Table 7 using village-level panel data are fairly similar to our main results where all villages are included. The impacts of access to electricity on total household income and nonfarm income are positive and significant and this effect is stronger for urban areas. In contrast, there is a weak negative association between farm income and household access to electricity; the coefficient of electricity is negative and not significant. Overall, our results are robust regardless of the sample composition.

TABLE 7. Impact of electrification on household income using village-panel data

	(1)	(2)	(3)
VARIABLES	**Total monthly income**	**Nonfarm income**	**Farm income**
All			
Electricity (1=yes)	0.352***	0.345	-0.142
	(0.120)	(0.253)	(0.169)
Observations	10,205	7,159	4,466
Urban			
Electricity (1=yes)	0.413**	0.280**	-0.0588
	(0.158)	(0.131)	(0.234)
Observations	7,086	5,716	1,771
Rural			
Electricity (1=yes)	0.179	0.389*	-0.154
	(0.159)	(0.199)	(0.166)
Observations	3,119	1,443	2,695

Note: The dependent variables are (1) log of total monthly income, (2) log of nonfarm income, (3) log of farm income, and (4) log of other income. The control variables at individual, household, and village levels are included. District and year fixed effects are included. All errors are clustered at village level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6.2. Spillover benefits to non-electrified households

One question in any village electrification project is whether non-electrified households derive benefits from such a project. Non-electrified households living in electrified villages are marginalized members of the community because they live in remote areas far from the connection grid or are too poor to pay for the fixed cost of connection. We argue that non-electrified households within electrified villages may experience a change in their outcomes related to employment and household income as a result of village electrification, "the spillover benefits". In this analysis, our treated group corresponds to non-electrified households in electrified villages; control households are households in non-electrified villages. That is, we excluded electrified households in electrified villages in our estimations. Estimation strategies are the same as Equations (2) and (3) in Section 4 and our interest variable is the binary variable village connected to grid electricity, rather than access to electricity at the household level.

Table 8 shows the results of IV estimations for spillover effects of village electrification on outcomes related to employment. Individuals in non-electrified households located in an electrified village have a higher probability of engaging in wage employment and self-employment in the nonfarm sector. By contrast, it shows that village electrification decreases self-employment in the farm sector and unpaid family work. The findings suggest that there were changes in local labor market conditions that generated new employment opportunities, which in turn prompted more people to enter either the wage labor market or self-employment in the nonfarm sector. These labor market improvements benefit all households including the non-electrified households in a village that is hooked to a grid. Village electrification creates jobs which we consider the "spillover benefits" of village electrification to non-electrified households.

TABLE 8. Village-level effect of electrification on employment

	All			
	(1)	(2)	(3)	(4)
VARIABLES	**Wage employment**	**Self-employment in nonfarm sector**	**Self-employment in farm sector**	**Unpaid family worker**
Village_Electricity (1=yes)	0.285*** (0.103)	0.228* (0.126)	-0.373** (0.161)	-0.312*** (0.0920)
Individual level				
Female (1=yes)	-0.0685*** (0.00545)	0.0104*** (0.00347)	-0.106*** (0.00756)	0.0924*** (0.00590)
Age	0.0236*** (0.00163)	0.00179 (0.00137)	0.0336*** (0.00189)	-0.0217*** (0.00134)
Age_squared	-0.000359*** (2.23e-05)	-1.74e-05 (1.90e-05)	-0.000324*** (2.66e-05)	0.000218*** (1.76e-05)
Married (1=yes)	-0.115*** (0.00800)	0.0216*** (0.00744)	0.132*** (0.0101)	-0.0384*** (0.00643)
Years of education	0.00193*** (0.000727)	0.00951*** (0.000815)	-0.0144*** (0.00103)	-0.000199 (0.000569)
Household level				
Urban (1=yes)	0.0207 (0.0545)	0.00917 (0.0580)	-0.0908 (0.0741)	0.0532 (0.0375)
Number of toddlers	0.00374 (0.00391)	0.0116** (0.00488)	-0.00944 (0.00595)	-0.0209*** (0.00280)
Size of irrigated land	-0.000763** (0.000326)	-0.000440 (0.000536)	0.000963 (0.000598)	0.000171 (0.000333)
Village level				
Distance_bus_stop	-8.62e-05 (0.000238)	-0.000676** (0.000272)	4.45e-05 (0.000350)	0.000464** (0.000236)
Village_factory (1=yes)	-0.0204 (0.0152)	0.00497 (0.0181)	-0.00173 (0.0238)	0.0261* (0.0133)
Village_Infrastructure (1=yes)	-0.0392** (0.0177)	0.0116 (0.0219)	0.0155 (0.0285)	0.0395** (0.0153)
Observations	60,217	60,217	60,217	60,217
R-squared	0.005	-0.010	0.099	0.026
District fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

***$p<0.01$, **$p<0.05$, *$p<0.1$

In order to check the consistency of the results with the data from the labor demand side, we extracted the CSES survey villages from the ECC 2011 and 2014 and matched them with the village electrification status from CSES in 2009 and 2014. We find that firm size and the percentage of formal firms in electrified villages are larger than those in non-electrified villages. These findings are consistent with household income sources using the CSES data (Table 1) that the proportion of income from wage employment especially in service sectors increased to 41 percent in 2014, suggesting that the number of labor-intensive jobs that employ a large number of workers in wage employment has increased in electrified villages. Clearly, electrification induces positive changes in the labor market through job creation.

Overall, our analysis confirms the presence of spillover benefits from village electrification to non-electrified households, especially in terms of employment. Furthermore, we confirm a demand effect working through changes in local labor market conditions: electrification induced the creation of wage employment especially in the service sector in electrified villages.

7. Conclusion

Cambodia, one of the fastest-growing economies in Southeast Asia, recognizes an inadequate supply of electricity as one of the key obstacles to its economic development. Given the numerous recent enhancements of electrical grid infrastructure in developing countries, it is important to understand how access to electricity has impacted household welfare. This study examines the impacts of access to electricity on employment of the working-age population and various sources of household income. Using the IV approach, we obtained estimation results that suggest a strong and positive effect of household electrification, for both women and men, on wage employment and self-employment in the nonfarm sector. With regard to household income, our findings indicate that increased access to electricity contributes to total household income growth through an increase in nonfarm income. Furthermore, the effect of electrification on income growth is much stronger in urban areas. These results are consistent with estimation results using village panel data; and the analysis of the spillover effect of village electrification. In addition, the descriptive analysis using the data from the labor demand side shows that labor-intensive jobs that employ a larger number of workers in wage employment are expanding in electrified villages. It appears that the development of the nonfarm sector has been positively affected by the expansion of electricity. Such development has created jobs in the wage sector, which appears to be the main pathway through which electricity has impacted household welfare.

In brief, our findings show that electrification has facilitated a shift of household economic activities away from self-employment in the farm sector and unpaid work to wage work and self-employment in the nonfarm sector, and such a shift appears to have been the main driver of household income growth. These results suggest that electricity projects, by creating jobs and stimulating the development of the nonfarm sector, could serve as an effective instrument in improving household welfare. Inasmuch as labor is the main asset of the poor, expanding access to the national electric grid has a clear positive impact on poverty reduction. In light of all of these, it is essential to give top priority to the energy sector in policy discussions related to development in other areas of the developing world.

Acknowledgments: This work was supported by the Japan Society for the Promotion of Science KAKENHI Grant Number 20191175.

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The Philippine Review of Economics
62(1):77-111. DOI:10.37907/4ERP5202J

Do cash transfers mitigate risks and crowd out informal insurance? Evidence from a randomized experiment in the Philippines

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This study evaluates the impact of a Conditional Cash Transfer (CCT) program on risk mitigation and informal insurance systems among poor Filipino households during exposure to negative income shocks. CCTs can reduce dependence on informal arrangements by increasing beneficiaries' income, making them more resilient to shocks and less reliant on informal networks. Conversely, it can reinforce informal arrangements by enhancing the financial capacity of eligible households, enabling them to lend money to others during shocks. Theoretical outcomes can thus be ambiguous. Using a sample of 1,415 households from 130 village clusters randomly assigned to treatment and control groups, intention-to-treat (ITT) estimates suggest that CCT has unintended consequences on risk mitigation and positive spillover effects on the informal system. Beneficiaries' medical expenses and borrowings from the informal system increased during shocks. Additionally, increased lending support was observed among ineligible households in treatment areas, along with a decrease in their borrowings from the informal system.

JEL classification: O1, P36
Keywords: cash transfer, informal insurance, income shocks

1. Introduction

Poor households in both rural and urban areas of low-income countries face a myriad of challenges arising from various types of shocks, including aggregate events like natural disasters, pest and disease outbreaks, as well as idiosyncratic shocks such as death [Dercon et al. 2006], illness (Gertler and Gruber [2002]; Mehmood [2021]), and job loss (Skoufias and Parker [2006]; Morduch, [1999]).

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These adverse shocks can significantly diminish household incomes. In response, poor households employ a range of ex-ante and ex-post self-coping strategies, such as distress sales of assets, increased labor supply, migration for employment opportunities, reduced consumption by cutting back on non-essential expenses, and intertemporal resource allocation through borrowing and savings. However, these self-coping mechanisms often fall short in providing complete recovery from the impact of the shock.

Another common strategy adopted by households to cope with financial hardships is through informal arrangements within their social networks, commonly observed among extended families, ethnic groups, and neighbourhoods [Dercon 2002]. For instance, Fafchamps and Lund [2003] examined risk-sharing arrangements, such as gifts, loans, and asset sales, among rural Filipino households in four villages in the Cordillera Mountains of northern Philippines. Their research revealed that gifts and loans from friends and relatives served as effective risk-coping mechanisms during shocks, while informal insurance helped households manage the financial burden of funerals. However, these arrangements had limited impact on coping with shocks induced by crop failure, minor illnesses, or unemployment of household members other than the household head and spouse. Covariate shocks inherently challenge informal insurance mechanisms due to liquidity constraints and limits on aggregate resources. However, some evidence suggests that informal insurance could work under covariate shocks given certain conditions. Informal system is possible under covariate stress if accompanied by microinsurance and index insurance [Mobarak and Rosenzweig 2012]. While there may be temporary breakdowns after covariate shocks, informal networks can be restructured with new link formations, hence, may continue their existence [Ambrus et al. 2014].

CCT programs also function as a form of coping mechanism. Conceptually, CCTs entail government subsidies for education, health, and food, contingent upon compliance with certain conditions related to improvements in health and educational outcomes. These cash transfers have been shown to mitigate various shocks, such as school dropout rates [de Janvry et al. 2006] and teenage pregnancies [Baird et al. 2010]. However, the spending of these transfers is ultimately at the discretion of the household. Indeed, evidence indicates that cash transfers can serve as safety nets during adverse events, such as negative weather shocks affecting agricultural production, as seen in countries like Zambia (Lawlor et al. [2019]; Asfaw [2017]), Niger (Premand and Stoeffler [2020]), Kenya (Dietrich and Schmerzeck [2019]), and Indonesia [Christian et al., 2018].

While there is ample evidence supporting the positive effects of CCTs on risk mitigation, recent studies have raised concerns about potential unintended adverse consequences. For example, Filmer et al. [2021] identified a negative externality on the health outcomes of non-beneficiary children in the Philippines, attributed to an increase in the price of perishable foods in local markets.

Similarly, Olinto et al. [2006] observed that CCTs potentially crowded out private food transfers and money/food transfers from non-governmental organizations in Nicaragua, particularly in instances where CCTs were sufficiently large, thereby affecting private networks and informal insurance schemes. This crowding-out phenomenon arises from households withdrawing from existing risk-sharing arrangements, particularly when informal insurance mechanisms are weak [Morduch 1999]. Consequently, it is essential to examine the impact of cash transfer programs on the pre-existing informal support networks provided by family, friends, and community members.

In examining the case of the Philippines, our study seeks to determine whether CCTs can effectively mitigate the negative income shocks experienced by poor households. Additionally, we aim to investigate whether CCTs have the potential to alter existing informal risk-sharing arrangements between beneficiaries and non-beneficiaries of cash transfer programs in the presence or absence of negative income shocks. Specifically, while Filmer et al. [2021] attribute negative consequences for non-beneficiaries to higher food prices in treated areas, we explore another potential channel whereby negative outcomes for non-beneficiaries are exacerbated through the reduction of informal risk-sharing in treated areas.

Our approach is aligned with several studies that have investigated similar phenomena. For instance, Olinto et al. [2006] examine two scenarios of cash transfer programs—one where the CCT program is substantial enough to influence private transfers and another where the CCT program is too small to significantly impact private transfers. They identify two distinct effects on private transfers, including remittances and transfers from non-governmental organisations. In our analysis, we focus specifically on the crowding-out effects of CCTs, particularly considering the conditions under income shocks. Furthermore, we delve into the impact of informal arrangements within networks of friends and community members, as opposed to private transfers from non-government organizations (NGOs), as informal safety nets have been shown to effectively protect poor households from irreversible shocks as evidenced by studies in the Philippines [Fafchamps and Lund 2003], Ethiopia, and Tanzania [Dercon et al. 2006]. Alatas et al. [2012] find in their experimental study in Indonesia that treated households increased informal transfers to others through their informal network and that the spillover effects were measurable in nearby households. Moreover, Haushofer and Shapiro [2018] analysed the impact of unconditional cash transfers on both recipients and non-recipients within the same communities and found spillover effects to ineligible households in villages where others received cash transfers through informal sharing mechanisms.

The main findings of our study suggest that CCTs have the potential to strengthen the informal support system. We observe an increase in borrowings and lending among eligible households, indicating that CCTs have improved the creditworthiness and financial capacity of these households. Conversely, we find a decrease in borrowings and an increase in lending among ineligible households, suggesting that CCTs have diminished the confidence of ineligible households in borrowing money due to uncertainty regarding their economic conditions. Nevertheless, the trust in eligible households to repay debts remains high, leading to an increase in lending from ineligible households to eligibles within the informal system.

Our study contributes to several strands of literature. First, while existing studies have explored the impact of public transfers on informal transfers, the findings have been mixed. In contrast to some previous research, our study reveals that CCT recipients actually increased their borrowing. Theoretically, CCTs could enhance households' self-financing capacity, potentially reducing their reliance on informal arrangements. However, CCTs may also bolster households' financial standing, prompting them to support neighbors and friends, thereby reinforcing informal arrangements. This latter effect is particularly pronounced when norms of sharing are strong. Much of the evidence suggests that replacing informal risk protection mechanisms with government cash transfers in low- and middle-income countries could lead to social welfare losses [Nikolov and Bonci 2020]. However, in contexts such as rural Suriname and French Guiana, public transfers strengthened informal insurance systems when informal risk-sharing arrangements proved insufficient in addressing persistent adverse conditions like physical disabilities [Heemskerk et al. 2004]. Similarly, in Tanzania, a formal cash transfer program did not crowd out informal safety nets; instead, it encouraged beneficiary households to engage with them [Evans and Kosec 2020]. While acknowledging this evidence, our study adds to the literature by examining the impact of the Philippines CCT program to determine whether it leads to crowding-out effects or generates positive spillover effects in informal social safety nets.

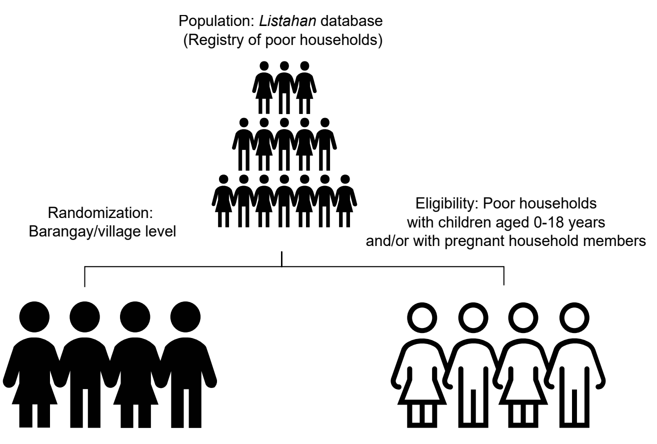
Second, the literature identifies the presence of unintended consequences of cash transfers, such as stunting among non-beneficiary children in the Philippines [Filmer et al. 2021], child labor in Mexico [de Janvry et al. 2006], and teenage pregnancies in Malawi [Baird et al. 2010]. Our study contributes to this growing literature by providing insights into the differential effects of cash transfer programs on beneficiaries and non-beneficiaries. While Albarran and Attanasio [2003] evaluated the impact of a cash transfer program in Mexico, they assumed that the crowding effect was consistent for both beneficiaries and non-beneficiaries. In contrast, our study analyzes the disparity in the average outcomes of the program for beneficiary and non-beneficiary groups.

Finally, we emphasize the effects of CCTs on risk events or shocks, particularly harvest failure. Our findings indicate that while negative income shocks impact consumption levels in poor households in the Philippines, CCTs have a risk-mitigating impact on recipient households. Additionally, we observe a positive spillover effect among ineligibles in treated areas when covariate shocks occur, as they increase lending support to informal insurance and decrease borrowings to avoid exhausting the resources of the informal risk-sharing network. The decrease in borrowings from the informal network among ineligibles suggests that during shocks, their confidence in their ability to repay loans may diminish due to uncertainty about their economic conditions, leading them to be reluctant to borrow from informal insurance systems. Therefore, ineligibles may perceive that excessive borrowing could deplete the network's resources, rendering it unsustainable and ineffective during shocks. Thus, our findings suggest that CCTs have the potential to strengthen the informal system, and these results remain robust across various specifications.

1.1. Background and RCT setting

As large-scale cash transfer programs gained traction in Latin America and Africa, similar initiatives emerged in Southeast Asia, including Indonesia and the Philippines. The Pantawid Pamilyang Pilipino Program (4Ps) was introduced by the Philippines government's Department of Social Welfare and Development (DSWD) in 2008 as a response to the food, fuel, and global financial crises. A randomized experiment was conducted to evaluate the program's impact on health and educational outcomes. The eligibility criteria for the program's treatment group included households with children aged 0 to 18 years and/or pregnant household members. Household poverty status was determined using scores from the Proxy Means Test (PMT), which predicts household income based on socioeconomic indicators such as household demographics, education, occupation, housing conditions, access to basic services, asset ownership, and location. Households with PMT scores below the poverty threshold were classified as poor and listed in *Listahanan*, a population database and official registry of poor households that is utilized in various government programs, including the PhilHealth Universal Health Care program.

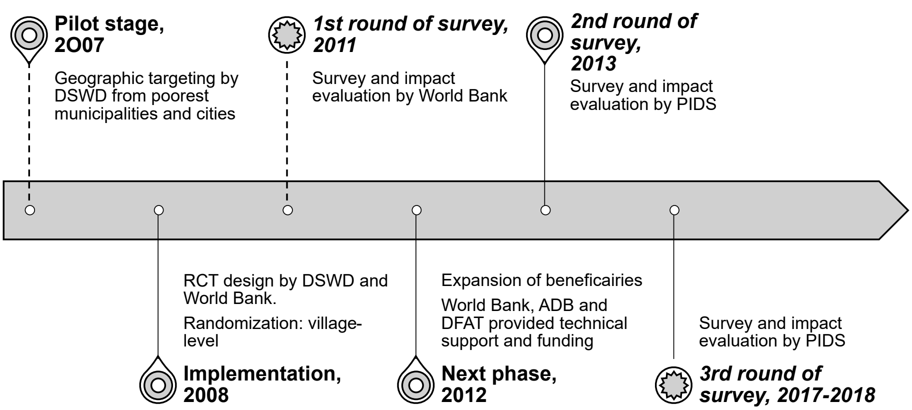
FIGURE 1. RCT design



Similar to CCT programs in other countries, eligible households under the 4Ps are required to meet specific conditions to receive cash grants. These conditions include ensuring immunization of children, monitoring their weight and deworming, receiving pre- and postnatal care, accessing delivery services from skilled health professionals for pregnant mothers, and ensuring 85 percent school attendance for children attending kindergarten, elementary, and high school. Parents are also required to attend monthly family development seminars aimed at promoting family and community development. Once these conditions are met, the eligible household receives various benefits, including a school fee allowance for up to three children, a budget for basic maternal and child health services, and a rice subsidy. Specifically, the household receives ₱300 per child attending kindergarten and elementary school, ₱500 for children attending high school, ₱500 for basic maternal and child health services, and ₱500 for rice subsidies on a monthly basis.

Initially, the program was piloted in selected areas before being gradually expanded nationwide through a phased implementation approach. Unlike CCT programs in other countries, the initial implementation of 4Ps did not involve the development of baseline data. Instead, three rounds of ex-post sample surveys were conducted with the head of households serving as the main respondent in 2011, 2013, 2017, and 2018 to assess the program's impact on various health, education, and behavioral outcomes.[1] While an initial randomized controlled trial (RCT) design was employed in 2011 with random assignment of the program at the village level, ethical concerns arising from the experiment led to a later implementation stage adopting a non-RCT-based framework.

FIGURE 2. Timeline of implementation



[1] However, implementing an RCT for this program necessitates technical support from academia, government, and international organisations to guide the program implementer in executing the experiment properly. Therefore, the absence of baseline data may not have been a significant issue.

1.2. Data and sample survey

For this study, we extensively utilize data collected in 2011 from a population of 376,000 households covered during the initial phase of the program's implementation in 2008. The sample encompasses households both below and above the PMT poverty threshold in treated and control villages, which were either assigned to participate in the program or not. The total sample consists of 1,415 households from 130 villages, spanning eight municipalities and four provinces across three major islands of the Philippines. Specifically, eligible households below the PMT poverty threshold represent 581 observations from randomly assigned program (treated) villages, and 608 observations from non-program (control) villages. In contrast, the sample size of ineligible households (those above the PMT poverty threshold) includes 120 observations from the treatment village and 106 observations from the control village. We exclusively utilize the 2011 data, as follow-up surveys employed a regression discontinuity design for impact evaluation, which is not suitable for examining the differential impacts of CCT on eligible and ineligible households.

Overall, the sample comprises 130 village clusters from eight municipalities across the three major islands of the Philippines. The dataset also provides information regarding the proportion of eligible households in the treatment village receiving benefits from the cash transfer, which closely aligns with the program assignment at 94 percent.

The survey employed separate instruments for household heads, mothers, female household members with partners, school-aged children, school principals, rural health officers, barangay officials, and local government mayors. Questionnaires collected data on various socioeconomic characteristics, reproductive history and contraception, school participation and child labor, health and nutrition, anthropometric measurements of children aged 0 to 5 years, cognitive assessment tests, barangay characteristics, and local government characteristics.

1.3. Estimation strategy

Our goal is to maintain homogeneity among groups, so we separately examine the impacts of the program for eligible and ineligible households, leveraging the advantages of an RCT design. We compared households with PMT scores below the poverty threshold in the treatment village to those with PMT scores below the poverty threshold in the control village, applying the same approach for ineligible households, considering the randomized treatment assignment at the village level.

First, we assessed if the program could mitigate negative income shocks. To estimate the program's risk-mitigation effects, we conducted an intention-to-treat (ITT) estimation which focuses on the random treatment assignment. ITT was used since it is policy-relevant estimation that examines the average impact of exposure to the treatment rather than the uptake. The rate of non-compliance is moderate at eight percent in the below PMT group and 13 percent in the above PMT group. Given the low non-compliance rate, the ITT can be close to the average treatment effect. The risk-mitigation effects are estimated using the following equation:

$$Cons_{ij} = \beta_0 + \beta_1 T_j + \beta_2 (T_j \times IS_{ij}) + \beta_3\, IS_{ij} + \boldsymbol{X}_{ij}\, \theta + \omega_j + \epsilon_{ij}\ , \qquad (1)$$

where $Cons_{ij}$ represents the outcome indicator of household i's consumption in village j, separately estimated for eligible (below PMT poverty threshold) and ineligible (above PMT poverty threshold) households. We assessed per capita consumption, decomposed into food products (e.g., dairy, meat, alcohol) and non-food products (e.g., education, medical expenditures). Dairy and meat consumption indicates a potential improvement in living standards (because these items are relatively expensive), while alcohol consumption reflects changes in temptation goods. Total consumption, education, and medical expenditure per capita were transformed using natural logarithmic functions to make the distribution normal, while dairy, meat, and alcohol consumption per capita were transformed using inverse hyperbolic sine functions to preserve the meaning of zero values. Inverse hyperbolic sine is used for these variables instead of *log* transformation plus a small constant because it accommodates zeros without needing arbitrary adjustments.

T_j denotes the random treatment assignment in the program, while IS_{ij} is an income shock variable proxied by harvest failure due to typhoons, floods, and other weather-related disasters, considered exogenous. We excluded idiosyncratic shocks (e.g., illness, death of family members) from our estimations due to their likely endogeneity. $\boldsymbol{X}_{ij}$ is a vector of controls including household head's demographic characteristics (e.g., age, gender), household characteristics (e.g., size, durable asset index) and barangay characteristics (e.g., natural disaster index, log of barangay population and number of households). ω_j is fixed effects at the municipal level.

β_2 is the main coefficient of interest, estimating the differential impact of aggregate shocks on consumption between the treatment and control groups. It quantifies the risk-mitigation effects of program assignment. β_3 provides the estimate of the average impact of shocks on the control group's consumption, while β_1 measures the impact of the program on the consumption of households in the treatment group when there is no shock. θ is the vector of coefficients associated with the control variables.

Second, to more directly examine evidence of spillover effects on informal arrangements, we estimated two models to compare the impact of receiving grants from the CCT program. The first model is given by Equation (2). This allowed us to examine the average effect on the informal system and to explore if CCT potentially improves informal risk-sharing through an increase in the overall available funds in a community.

$$Informal_{ij} = \delta_0 + \delta_1\, T_j + \boldsymbol{X}_{ij}\theta + \omega_j + \epsilon_{ij}\ , \tag{2}$$

The dependent variable $Informal_{ij}$ represents money borrowed and lent by households i in village j, excluding gifts received and given (e.g., church donations), migrant remittances, borrowing from moneylenders (e.g., Bombay 5-6)[2] or borrowing against land as collateral. This is measured by continuous variables, such as the amount of money borrowed from and lent to neighboring households or relatives. Borrowing and lending are estimated separately to better understand the inflow and outflow of transactions in the informal system. We focused on the impact of informal borrowing and lending because gifts are minimal and are not received regularly. $\boldsymbol{X}_{ij}$ is a vector of controls including the household head's characteristics (e.g., age, gender, marital status, nature of employment, having a bank account, and having a loan), household characteristics (e.g., size, durable asset index, social insurance index including life, health, housing, and other social insurance schemes), barangay characteristics such as health facility index (including barangay health station, rural health center, traditional birth attendant, private clinic, government hospital, private hospital, barangay pharmacy, and private pharmacy), barangay population, and fixed effects at the municipal level. These vectors of controls are included to adjust for imbalances from random differences.

δ_1 indicates whether the program crowds in or out informal arrangements. A positive δ_1 denotes that the program increases the household's total available funds (supply), and community demand provides positive spillover effects to households belonging to informal risk-sharing schemes, while a negative δ_1 suggests the opposite. Regarding borrowing outcomes, a negative coefficient implies that CCT is effective in reducing financial vulnerability by making eligible households less reliant on borrowing. Conversely, a positive coefficient may indicate that CCT has improved the creditworthiness of eligible households, encouraging ineligible households in the informal network to lend money to them, anticipating that the borrowings will be repaid in the future.

As it is not possible to identify if program-eligible households increase or decrease informal arrangements with ineligible households within a village, we again estimated Equation (2) separately for eligible households (i.e., those below the PMT threshold) and ineligible households (i.e., those above the PMT threshold). We expect that when we observe a positive δ_1 for outflows among eligible households, we will also see a positive δ_1 for inflows among ineligible households in the case of positive spillovers.

Out of the 1,189 observations that fall below the PMT, 636 observations (53 percent of poor households) reported positive borrowing from, and 46 observations (four percent of poor households) reported positive lending to

[2] The variable for borrowings from moneylenders is included to illustrate another typical coping mechanism among poor households in the Philippines.

informal systems, respectively, through friends and relatives. In contrast, among the sample size of 226 observations that fall above the PMT, 128 observations (only 57 percent of "near-poor" households) reported borrowings from, and 26 observations (seven percent of "near-poor" households) lent to informal systems, respectively, through friends and relatives.

As it is not possible to take the log for these observations due to the significant number of zeros, we used the inverse hyperbolic sine or arcsine transformation. For outcomes using the inverse hyperbolic sine transformation, we consistently employed Tobit regression to censor the outcome variables at lower limits. The estimates from this Tobit regression represents the effect of the independent variables on the latent variable y_i^* which has values censored at lower limits. They do not represent the effect of independent variables on the probability of being censored or the expected value of the observed outcome variables. Hence, the coefficients are not marginal effects.

We used the second model to examine if the program causes households in treated villages to leave, stay but reduce their engagement, or stay and engage with the informal insurance system when there is an income shock, represented by harvest failures. This helped us identify the mechanism by which the program reduces vulnerability to common shocks through engagement in risk-sharing activities. The estimation model is given by

$$Informal_{ij} = \alpha_0 + \alpha_1\, T_j + \alpha_2\, (T_j \times IS_{ij}) + \alpha_3\, IS_{ij} + \boldsymbol{X}_{ij}\theta + \omega_j + \epsilon_{ij}\,, \qquad (3)$$

In this model, α_2 captures the ITT spillover effects of the program on informal arrangements. We expect CCT-eligible households to contribute to the informal system in which poor households are likely to adopt risk-coping mechanisms when covariate shocks occur. It is also likely that program eligibles will reduce their reliance on the informal insurance system, contingent on the strength or enforceability of the sharing norm. A positive coefficient, α_2, can be expected from an increase in lending from CCT eligibles, largely driven by cash flows received from the program. It can also be expected from an increase in borrowings after proving their credibility for debt repayment. Debt repayment credibility within a community positively influences an individual's ability to better access and manage credit. However, it is also possible that there will be no change in the lending or borrowing transactions if the cash received from the program is sufficient to mitigate the risk from covariate shocks.

The mechanisms that are directly examined through the empirical methodology are the changes in the informal risk-sharing network resulting from CCT, particularly the changes in the borrowings and lending of eligible and ineligibles. We specifically consider the following conceptual framework that describes possible reasons why borrowings and lending of eligibles and ineligibles increase or decrease, with a visual diagram provided in Figure 3.

a. Borrowing from informal insurance among eligible households increases if: (1) creditworthiness improves due to the regular cash transfers received from CCT. In such cases, ineligibles within the informal network are motivated to lend to eligibles, especially in times of need. (2) The anticipation and assurance that borrowings will be repaid by the eligibles in the future facilitate an increase in their borrowings. (3) Sharing norms is strong, there is an increase of support from ineligibles to the informal network.
b. Lending to informal insurance among eligible households increases if: (1) CCT increases the financial capacity of eligibles, allowing them to lend money to others in times of shock. (2) Eligibles aim to diversify risk during shocks, leading to increased lending to the collective fund in the informal insurance.
c. Borrowing from informal insurance among eligible households decreases if: (1) CCT eligibles experience improved economic conditions due to the benefits they receive from CCT, enabling them to reduce borrowing from informal insurance. Experiencing financial stability due to CCT benefits leads the eligibles to diminish the need for borrowing from informal insurance. (2) Improved creditworthiness among CCT eligibles, resulting from CCT benefits, may grant them access to formal financial resources such as bank loans, reducing their reliance on informal insurance. (3) CCT can inadvertently increase implicit interest rates in informal network (e.g., Torkelson [2000]; Bold et al. [2012]) causing borrowings of the eligible households in the informal network to decrease.
d. Lending to informal insurance among eligible households decreases if: (1) CCT eligibles invest more in opening small businesses since CCT program implementers assist them in creating their own businesses. Consequently, instead of putting their money into the informal network through lending, they may reduce lending and allocate funds to their businesses as investments. (2) During shocks, eligibles may experience a sudden loss of income, limiting their ability to contribute to informal insurance. In such instances, if there is an increased demand for immediate cash during shocks, eligibles might prioritize basic needs, medical costs, and other necessities over contributing to communal funds in the informal network.
e. Borrowings from informal insurance among ineligible households increase if: (1) CCT eligibles in the informal network lend support to ineligibles to help them manage risk when they face financial challenges or require immediate assistance from informal networks. (2) Other forms of coping mechanisms such as illegal money lending (e.g., loan sharks) or microfinance may not lend money to ineligibles,

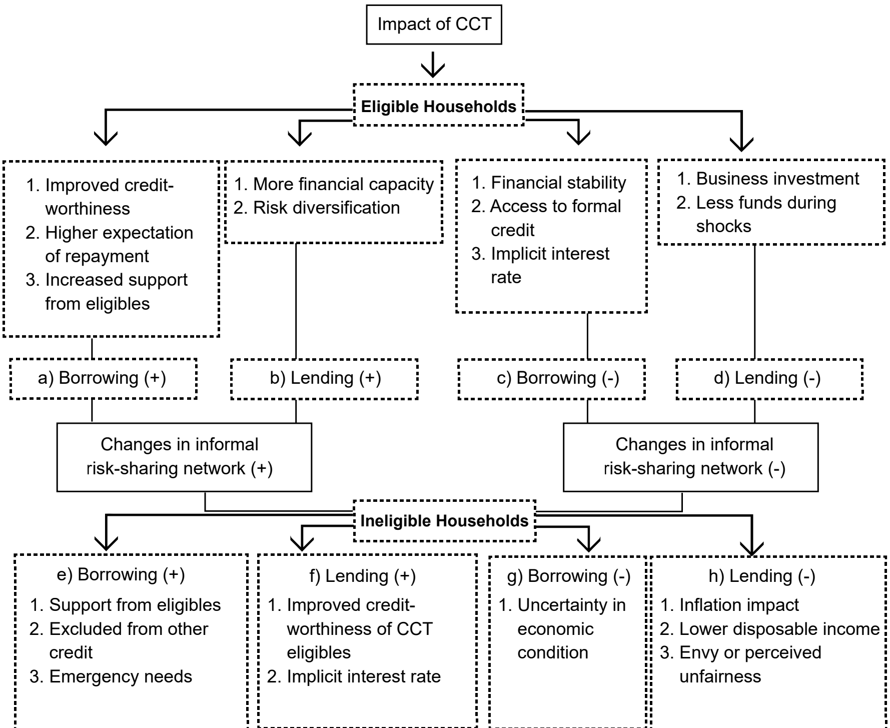
as these lending systems may prefer eligibles. In such cases, the only option for ineligibles may be informal insurance. (3) During shocks, ineligibles may require cash for house repairs, medical costs, and purchasing essential goods, especially when regular income is disrupted.

f. Lending to informal insurance among ineligible households increases if: (1) ineligibles trust CCT eligibles in the informal network because they receive benefits from CCT. Consequently, lending by ineligibles in the informal network increases. (2) CCT can inadvertently increase implicit interest rates in the informal network as eligible households will be viewed by ineligible households to be richer. This encourages ineligible households to increase their lending to the informal network.
g. Borrowings from informal insurance among ineligible households decrease if, during shocks, the ineligibles' confidence in their ability to repay loans is low due to uncertainty in their economic condition. In such cases, they may be reluctant to borrow from informal insurance systems.
h. Lending to informal insurance among ineligible households decreases if: (1) CCT results in upward pressure on prices of goods and services in the local market, negatively affecting ineligibles' income, leading to a decrease in lending to the informal network. (2) During shocks, ineligibles may face economic hardship, leading to a reduction in disposable income. Hence, their limited income may be redirected towards immediate personal needs rather than contributions to informal insurance systems. (3) perceptions of inequality or unfairness, such as envy towards eligible households (e.g., Fafchamps and Lund [2003]; Dercon, et al. [2006]) persist.

The validity of these different consequences can be assessed with the proposed model (equation 3) because (a) to (h) suggest scenarios for increase or decrease in borrowings and lending of eligibles and ineligibles of CCT who engage with the informal network when there is shock. We believe that these mechanisms are the underlying interactions among eligibles and ineligibles in the informal network since it is a system where individuals can support each other during times of crisis and borrowing and lending of money are the ways to support each other within the informal system.

Since the theoretical consequences are not unique, this is an empirical question. Again, we estimated Equation (3) separately for eligible (PMT below the threshold) and ineligible (PMT above the threshold) households.

FIGURE 3. Pathways linking CCT to informal insurance



1.3.1. Summary statistics

Table 1 presents the mean differences between treatment and control households, separately for samples below and above the PMT threshold in 2011. A detailed description of the variables used can be found in Appendix C. The null hypothesis of equal means was rejected for four of the 21 and five out of 21 pre-determined characteristics used in the estimation model for samples below and above the PMT threshold, respectively. These differences may be attributed to the small sample variation at the provincial level, as it covers only four provinces. However, these four provinces are representative of the three major islands in the Philippines: Luzon, Visayas, and Mindanao. Among the covariate shock variables, the household-level shock shows balance, but the village-level shocks such as flood and drought show imbalance between the treatment and control groups. The means of flooding and drought are higher in the treatment group, suggesting that treatment villages are more prone to flooding and drought than control villages for both the below and above PMT groups. To address this concern, a sub-group analysis will be presented after the main analysis. A love plot for standard mean difference (SMDs) is shown in Appendix D, indicating that SMDs are close to zero after matching.

TABLE 1. Balance on demographic characteristics, shocks, consumption outcome, and lending and borrowings outcomes

	Below PMT				
		(1) Treatment		(2) Control	(3) *t*-test Difference
Variable	**N**	**Mean [SE]**	**N**	**Mean [SE]**	**(1)-(2)**
Household head characteristics					
Age	581	43.114 [0.435]	608	43.400 [0.440]	-0.286
Gender (1=Female)	581	0.16 [0.02]	608	0.17 [0.02]	-0.01
Educational attainment (1=High school graduate)	555	5.90 [0.15]	585	5.87 [0.14]	0.03
Marital status (1=Married)	575	0.91 [0.021]	600	0.92 [0.01]	-0.01
Nature of employment (1=Permanent)	527	0.59 [0.02]	526	0.55 [0.02]	0.04
Household characteristics					
Household size	581	6.40 [0.09]	608	6.30 [0.09]	0.10
Durable asset index	581	1.30 [0.06]	608	1.41 [0.06]	-0.12
Has an outstanding loan (1=Yes)	581	0.52 [0.02]	608	0.55 [0.02]	-0.04
Has bank account (1=Yes)	573	0.07 [0.01]	595	0.08 [0.01]	-0.01
Insurance index (health, life, housing, and other social insurance)	581	0.95 [0.03]	608	0.77 [0.02]	0.18***
Barangay characteristics					
Health facility index (rural health center, clinic, hospital, pharmacy etc.)	581	1.85 [0.06]	608	1.84 [0.05]	0.02
Log of barangay population	558	7.27 [0.04]	566	7.33 [0.03]	-0.07
Log of number of households in barangay	558	5.66 [0.03]	562	5.76 [0.03]	-0.10**
Covariate shocks					
Harvest failure (household-level)	578	0.16 [0.02]	608	0.15 [0.02]	0.01
Flood (village-level)	581	0.587 [0.020]	608	0.510 [0.020]	0.077***
Earthquake (village-level)	581	0.621 [0.020]	608	0.635 [0.020]	-0.014
Drought (village-level)	581	0.484 [0.021]	608	0.411 [0.020]	0.072**
Natural disaster intensity (1=more than 2 disasters) (village-level)	581	0.549 [0.021]	608	0.536 [0.020]	0.013
Location characteristics					
Municipality (1=Basay)	581	0.076 [0.011]	608	0.082 [0.011]	-0.007
Province (1=Lanao Del Norte)	581	0.344 [0.020]	608	0.301 [0.019]	0.043

TABLE 1. Balance on demographic characteristics... (continued)

Below PMT					
		(1) Treatment		**(2) Control**	**(3) *t*-test Difference**
Variable	**N**	**Mean [SE]**	**N**	**Mean [SE]**	**(1)-(2)**
Outcome variables					
Household consumption					
Per capita consumption	581	14,284.845 [462.755]	608	14,097.627 [402.919]	187.218
Per capita education expenditure	579	379.363 [42.559]	607	382.947 [40.904]	-3.585
Per capita medical expenditure	578	281.613 [33.093]	608	245.736 [32.863]	35.878
Per capita of dairy consumption	579	496.929 [37.746]	608	428.041 [36.614]	68.888
Per capita of meat consumption	580	634.493 [40.224]	608	713.540 [43.449]	-79.047
Per capita of alcohol consumption	580	93.294 [11.258]	608	153.584 [19.034]	-60.289***
Total borrowings from and lending to friends and relatives	581	3,299.324 [478.562]	608	2,090.155 [517.152]	1209.169*
Borrowings from friends and relatives	581	4,017.757 [491.255]	608	3,923.434 [658.130]	94.323
Borrowings from moneylender	581	918.072 [209.745]	608	1900.220 [423.449]	-982.148**
Lending to friends and relatives	581	192.754 [108.288]	608	66.447 [17.584]	126.307
Borrowings from friends and relatives (1=Yes)	581	0.516 [0.021]	608	0.553 [0.020]	-0.036
Borrowings from moneylender (1=Yes)	581	0.102 [0.013]	608	0.138 [0.014]	-0.037*
Lending to friends and relatives (1=Yes)	581	0.041 [0.008]	608	0.036 [0.008]	0.005
Bank borrowings	581	1,206.540 [415.359]	608	1,473.487 [550.828]	-266.946
Above PMT					
Household head characteristic					
Age	119	46.345 [1.261]	106	44.670 [1.333]	1.675
Gender (1=Female)	120	0.275 [0.041]	106	0.151 [0.035]	0.124**
Educational attainment (1=High school graduate)	120	0.233 [0.039]	106	0.189 [0.038]	0.045
Marital status (1=Married)	120	0.758 [0.039]	105	0.848 [0.035]	-0.089*
Nature of employment (1=Permanent)	90	0.578 [0.052]	86	0.453 [0.054]	0.124

TABLE 1. Balance on demographic characteristics... (continued)

Above PMT					
		(1) Treatment		(2) Control	(3) *t*-test Difference
Variable	**N**	**Mean [SE]**	**N**	**Mean [SE]**	**(1)-(2)**
Household characteristics					
Household size	120	4.600 [0.178]	106	4.462 [0.169]	0.138
Durable asset index	120	3.292 [0.205]	106	3.349 [0.247]	-0.057
Has an outstanding loan (1=Yes)	120	0.550 [0.046]	106	0.585 [0.048]	-0.035
Has bank account (1=Yes)	118	0.280 [0.041]	101	0.188 [0.039]	0.092
Insurance index (health, life, housing, and other social insurance)	120	1.200 [0.081]	106	0.868 [0.076]	0.332***
Barangay characteristics					
Health facility index (rural health center, clinic, hospital, pharmacy etc.)	120	2.158 [0.125]	106	2.274 [0.135]	-0.115
Log of barangay population	120	7.530 [0.093]	95	7.510 [0.079]	0.020
Log of number of households in barangay	120	5.813 [0.077]	97	5.821 [0.075]	-0.009
Covariate shocks					
Harvest failure (household-level)	120	0.150 [0.033]	106	0.085 [0.027]	0.065
Flood (village-level)	120	0.658 [0.043]	106	0.462 [0.049]	0.196***
Earthquake (village-level)	120	0.617 [0.045]	106	0.717 [0.044]	-0.100
Drought (village-level)	120	0.492 [0.046]	106	0.321 [0.046]	0.171***
Natural disaster intensity (1=more than 2 disasters) (village-level)	120	0.567 [0.045]	106	0.519 [0.049]	0.048
Location characteristics					
Municipality (1=Basay)	120	0.100 [0.028]	106	0.057 [0.023]	0.043
Province (1=Lanao Del Norte)	120	0.217 [0.038]	106	0.189 [0.038]	0.028
Outcome variables					
Household consumption					
Per capita consumption	120	28,762.549 [2763.593]	106	32,902.831 [3,978.807]	-4,140.282
Per capita education expenditure	120	1,382.998 [470.779]	106	992.498 [222.719]	390.500
Per capita medical expenditure	120	2,024.836 [1254.856]	106	899.277 [283.392]	1,125.559

TABLE 1. Balance on demographic characteristics... (continued)

Above PMT					
		(1) Treatment		(2) Control	(3) *t*-test Difference
Variable	**N**	**Mean [SE]**	**N**	**Mean [SE]**	**(1)-(2)**
Per capita of dairy consumption	120	896.433 [140.584]	106	991.619 [162.618]	-95.186
Per capita of meat consumption	120	1,679.531 [195.289]	106	1,729.406 [318.328]	-49.875
Per capita of alcohol consumption	120	138.886 [29.733]	106	505.766 [150.959]	-366.881**
Total borrowings from and lending to friends and relatives	120	2,116 [523.742]	106	3,790.566 [1029.648]	-1,674.566
Borrowings from friends and relatives	120	377.750 [177.413]	106	413.208 [298.123]	-35.458
Borrowings from moneylender	120	1,095.833 [391.448]	106	9,048.113 [5,749.650]	-7,952.280
Lending to friends and relatives	120	2,750.750 [601.821]	106	12,283.962 [5,793.592]	-9,533.212*
Borrowings from friends and relatives (1=Yes)	120	0.550 [0.046]	106	0.585 [0.048]	-0.035
Borrowings from moneylender (1=Yes)	120	0.300 [0.042]	106	0.415 [0.048]	-0.115*
Lending to friends and relatives (1=Yes)	120	0.083 [0.025]	106	0.057 [0.023]	0.027
Bank borrowings	120	6,600 [2,185.527]	106	2,000 [1,021.688]	4,600*

Note: Insurance index, health facility index and natural disaster index are created by summing multiple variables for each observation. Insurance index covers health, life, housing, and other social insurance (index ranged from zero to four). Health facility index covers the presence of barangay health station, rural health unit, traditional birth attendant, private clinic, government hospital and pharmacy in the barangay or village (index ranged from zero to six). Natural disaster intensity is equal to one if village suffered from more than two disasters, which covers either flood, earthquake, or drought).
The values displayed in the last column are *p*-values for *t*-tests for the equality of means across the groups. ***, **, and * indicate significance at the one percent, five percent, and ten percent levels, respectively. Standard errors in brackets.

4. Empirical results

4.1. Estimates of risk-mitigating effects

Table 2 presents the estimates of the program effect, covariate shocks, and risk-mitigating effects of the program on the natural logarithmic forms of total consumption per capita, education cost per capita, medical cost per capita, and the inverse hyperbolic transformations of dairy, meat, and alcohol consumption per capita. Panels A and B provide the results for eligible and ineligible households, respectively.

In Panel A, the results show that the program significantly increased the log of total consumption per capita and education expenditure per capita for eligible households. The consumption of dairy and meat products separately indicated an increase in food consumption, with high protein serving as a proxy for better living standards among the poor. Rice is the dominant staple in the Filipino diet, particularly in rural households. Protein-rich foods, such as dairy and meat, are relatively expensive for the poor; thus, improved income levels will likely increase the consumption of meat and dairy products (e.g., eggs, milk, butter, cheese). The program exhibits a positive consumption effect over virtuous or healthy products (e.g., dairy) and a negative effect on the consumption of sin or unhealthy products (e.g., alcohol in Panel A and Panel B).

These results are consistent with Hoddinott and Skoufias [2004], where they found that PROGRESA in rural Mexico enabled its beneficiaries to "eat better" by focusing on dietary quality rather than food quantity. The study further found a positive spillover to non-beneficiaries in the treatment localities due to the free flow of information within the community regarding good dietary practices.

The program reduces alcohol consumption because the eligible households focused on spending for education and health expenditures as conditionalities of the program. Moreover, continuous check-ups may have led to a lifestyle change. The Family Development Seminar (FDS) of the CCT program may train the eligibles to reduce spending on non-essential items and prioritize meeting basic needs such as food, health, and education as an incentive to sustain the benefits from the program. Similarly, Panel B also found a negative effect on the consumption of alcohol among the treatment group, suggesting the flow of information from eligibles to ineligibles regarding reduced spending on non-essential items, consistent with Hoddinott and Skoufias's [2004] findings.

TABLE 2. Risk-mitigating effects

	Log transformation of per capita			Arcsine transformation of per capita consumptions in		
	Total Consumption	Education cost	Medical cost	Dairy	Meat	Alcohol
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Eligible (below PMT)						
Program assignment (w/out covariate shock)	0.07* (0.04)	0.42* (0.22)	0.24 (0.26)	0.50*** (0.17)	0.05 (0.22)	-0.54*** (0.20)
Covariate shock (proxied by harvest failure)	-0.02 (0.08)	-0.20 (0.40)	-0.37 (0.46)	-0.63* (0.33)	-0.88** (0.38)	-0.92*** (0.29)
Program assignment X Covariate shock	-0.11 (0.10)	0.05 (0.51)	1.32** (0.60)	0.18 (0.43)	0.65 (0.50)	0.62 (0.46)

TABLE 2. Risk-mitigating effects (continued)

	Log transformation of per capita			Arcsine transformation of per capita consumptions in		
	Total Consumption	Education cost	Medical cost	Dairy	Meat	Alcohol
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Constant	9.35*** (0.24)	3.80*** (1.38)	-0.59 (1.64)	5.91*** (1.01)	6.33*** (1.32)	1.97** (0.97)
Observations	1,102	1,100	1,099	1,100	1,101	1,101
Pseudo R^2	0.150	0.0256	0.0198	0.0363	0.0239	0.0215
Panel B: Ineligible (above PMT)						
Program assignment (w/out covariate shock)	-0.13 (0.08)	0.52 (0.67)	0.06 (0.51)	0.20 (0.34)	-0.18 (0.39)	-1.18*** (0.40)
Covariate shock (proxied by harvest failure)	-0.15 (0.20)	-1.13 (2.74)	-0.94 (1.39)	0.22 (1.09)	0.09 (0.50)	-1.02 (1.20)
Program assignment X Covariate shock	0.41 (0.26)	0.56 (3.05)	1.95 (1.78)	0.27 (1.25)	-0.19 (0.74)	1.49 (1.37)
Constant	10.14*** (0.39)	0.45 (4.00)	2.36 (2.73)	7.86*** (1.71)	8.81*** (2.03)	4.40* (2.63)
Observations	211	211	211	211	211	211
Pseudo R^2	0.221	0.0725	0.0368	0.0422	0.0483	0.0297

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations.
**p*<0.01; ***p*<0.05; ****p*<0.001

The program's risk-mitigating effects, represented by the interaction term, are apparent in the cost of medical care such as drugs and medicines, hospital room charges, medical and dental charges, and other medical expenses of treated households when exposed to covariate shocks. Harvest failure substantially increased medical costs because it can lead to food shortages, causing malnutrition for residents in the village. A lack of essential nutrients makes individuals susceptible to disease or infection, thereby driving up medical costs for households. Given that health insurance coverage is limited in the Philippines, individuals often incur significant health costs, resulting in high out-of-pocket expenditures. The additional cash from the program may help alleviate the burden of medical expenses on poor Filipino households.

4.2. Estimates of informal transfers

Turning to the impacts on informal transfers, Table 3 presents the results of the spillover effects of CCT on the borrowing and lending behaviours of eligible and ineligible households. The model was also fitted for borrowing from formal sources to compare the spillover effects of CCT between informal and formal systems. Control variables, comprising household and barangay characteristics, and fixed effects at the municipal level were included in the model.

The inclusion of these control variables resulted in the omission of a few observations, further decreasing the number of observations to 966 below the poverty threshold and 161 above the poverty threshold. Approximately 19 percent of the observations were lost due to missing values on some covariates. To address this attrition problem, we examined if the omitted observations were random and found systematic differences in the average characteristics between the remaining and omitted observations. Thus, we estimated the non-attrition probit and used the inverse of the predicted value of non-attrition as weights (inverse probability weighting: IPW) to address the potential estimation bias (see Appendix A for the non-attrition probit estimation result).

The results suggest that CCT increased the engagement of its eligibles in informal borrowing and lending systems, as evidenced by the significant increase in total lending and borrowing in the informal system among eligible households. Eligibles of CCT also significantly increased their borrowings from formal banks (column 5), indicating that CCT may have improved their capability and credibility to borrow money from financial institutions. These results are consistent with the enhanced financial capacity of CCT eligibles due to the transfers.

On the other hand, CCT seems to have adversely affected the informal sharing schemes of ineligible households, as shown by the significant decrease in borrowing from friends. This result is also true with borrowings from moneylenders, commonly known in the Philippines as “loan sharks” or “5-6,” which are informal in nature. Hence, while ineligibles decrease their borrowings in the informal insurance system, they simultaneously reduce vulnerability to predatory lending practices, as lenders often take advantage of borrowers through excessive interest rates. This result can be explained by the fact that ineligibles also face uncertainty in economic conditions, lowering their confidence to repay borrowings.

The inverse probability weighting (IPW) estimates show consistent results in Panels A and B. In Panel A, the IPW estimate for total borrowings and lending in the informal insurance and formal borrowing are positive and significant, which are consistent with the unweighted Tobit estimate. Likewise in Panel B, the IPW estimate for borrowings from friends is negative, which is consistent with the unweighted Tobit estimate.

TABLE 3. Spillover effects of CCT on informal systems and other coping mechanisms

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	Borrowings from bank
VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel A: Eligible (below PMT)					
Program assignment (w/out covariate shock)	1.48**	2.73	-0.05	-3.05**	3.34*
	(0.65)	(2.27)	(0.48)	(1.49)	(1.82)
Constant	-21.93***	-102.05***	-38.96***	-80.77***	-119.03***
	(3.01)	(22.00)	(2.52)	(6.01)	(10.48)
Observations	966	966	966	966	966
Pseudo R^2	0.161	0.0756	0.264	0.142	0.186
IPW estimates					
Program assignment (w/out covariate shock)	1.43**	2.97	-0.14	-4.45**	3.79**
	(0.68)	(2.26)	(0.50)	(1.74)	(1.75)
Constant	-23.61***	-107.96***	-35.88***	-27.27***	-119.76***
	(3.35)	(26.78)	(2.68)	(7.45)	(11.16)
Panel B: Ineligible (above PMT)					
Program assignment (w/out covariate shock)	-0.60	3.63	-2.97*	-5.04*	3.06
	(2.16)	(4.39)	(1.67)	(3.00)	(3.98)
Constant	-17.70**	-3.65	-48.67***	-76.73***	-110.36***
	(7.40)	(15.29)	(7.04)	(14.27)	(15.71)
Observations	161	161	161	161	161
Pseudo R^2	0.0891	0.164	0.248	0.180	0.282
IPW estimates					
Program assignment (w/out covariate shock	-2.41	2.28	-3.47**	-6.68*	3.63
	(2.07)	(4.66)	(1.50)	(3.81)	(3.94)
Constant	-15.92**	1.64	-178.34***	-5.45	-103.46***
	(7.45)	(15.84)	(54.05)	(11.24)	(15.74)

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations. *p<0.01; **p<0.05; ***p<0.001

Table 4 presents the results for Equation (3). The inclusion of the shock variable and controls from Equation (2) in Equation (3) has resulted in the omission of a few more observations, reducing the sample size to 963 for households below the poverty threshold and maintaining the same sample size of 161 for households above the poverty threshold. This result is consistent with the findings from Table 3, indicating that CCT has a positive and significant impact on total lending and borrowing in informal and formal systems among eligible households.

TABLE 4. Spillover effects of CCT on informal systems and other coping mechanisms in the presence of shocks

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	Borrowings from bank
VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel A: Eligible (below PMT)					
Program assignment (w/out covariate shock)	1.13* (0.67)	2.01 (2.45)	-0.39 (0.47)	-3.96** (1.56)	4.46** (1.93)
Covariate shock (proxied by harvest failure)	-2.09 (1.50)	-4.61 (5.03)	-2.13** (0.98)	-2.41 (2.59)	1.13 (3.82)
Program assignment X Covariate shock	2.7 (2.29)	6.32 (6.62)	2.63* (1.49)	6.99* (3.63)	-10.92* (5.75)
Constant	-21.23*** (3.06)	-100.72 (0.00)	-38.08*** (2.56)	-79.74*** (6.28)	-113.87*** (9.79)
Observations	963	963	963	963	963
Pseudo R^2	0.162	0.0771	0.265	0.144	0.192
IPW estimates					
Program assignment (w/out covariate shock)	1.53 (1.08)	1.93 (3.63)	-0.28 (0.45)	-4.45** (1.74)	5.55** (2.53)
Covariate shock (proxied by harvest failure)	-4.81* (2.78)	-8.17 (8.31)	-1.68* (0.91)	-1.66 (2.90)	3.84 (4.57)
Program assignment X Covariate shock	9.29** (3.98)	17.75** (7.52)	2.43* (1.44)	6.41 (4.18)	-19.96*** (6.41)
Constant	-29.70*** (5.01)	-33.13*** (10.95)	1.06 (2.15)	-27.27*** (7.45)	-43.26*** (9.00)

TABLE 4. Spillover effects of CCT on informal systems and other coping mechanisms in the presence of shocks (continued)

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	Borrowings from bank
VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel B: Ineligible (above PMT)					
Program assignment (w/out covariate shock)	-1.38 (2.16)	-0.05 (4.51)	-2.33 (1.73)	-4.84 (3.23)	2.48 (4.01)
Covariate shock (proxied by harvest failure)	-2.95 (5.25)	3.45 (9.32)	5.32** (2.58)	-3.06 (9.64)	-40.60*** (7.83)
Program assignment X Covariate shock	8.12 (5.76)	18.29 (11.45)	-9.31** (4.68)	-0.33 (11.81)	41.98*** (9.08)
Constant	-18.81** (7.71)	4.01 (14.92)	-47.42*** (7.05)	-74.85*** (15.54)	-104.17*** (15.05)
Observations	161	161	161	161	161
Pseudo R^2	0.0922	0.197	0.252	0.181	0.287
IPW estimates					
Program assignment (w/out covariate shock	-2.90 (2.03)	-1.26 (4.59)	-2.88* (1.51)	-5.30 (3.93)	3.00 (4.07)
Covariate shock (proxied by harvest failure)	-4.39 (4.99)	0.30 (9.92)	4.28* (2.25)	-1.55 (9.56)	-40.72*** (7.81)
Program assignment X Covariate shock	8.90 (5.71)	22.64* (12.40)	-7.78* (3.95)	-9.39 (12.32)	44.68*** (9.19)
Constant	-18.12** (7.38)	7.93 (15.40)	-42.08*** (6.15)	-2.96 (13.06)	-104.16*** (15.46)

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations.*p<0.01; **p<0.05; ***p<0.001

Panel A of Table 4 confirms the positive effect of CCT on the informal system among eligible households, wherein eligibles increase their borrowing during income shocks (column 3). The average daily income of individuals at the poverty threshold is ₱80.20 per day per person. Hence, a significant increase of 2.6 percent borrowings is economically significant. Since there was a significant number of zero borrowings (47 percent of the observations from above PMT observations and 43 percent from below the PMT), borrowings are highly skewed. However, arcsine transformation reduced the distortion of zero values and improved the model's fit.

Eligibility to receive money from the government may improve eligibles' borrowing credibility in informal risk-sharing because they are expected to consistently pay off their debt over time. CCT also seems to attract loan sharks during shocks as borrowing from moneylenders increased. The influx of cash into the community seems to attract the attention of loan sharks and gives them the opportunity to exploit the eligibles of CCT because of their access to more funds coming into the community through CCT. IPW estimates show a positive and significant increase in lending to friends and relatives, and total lending and borrowing show positive coefficients during shocks. This suggests that CCT increases the financial capacity of eligibles, allowing them to lend money to others when there is a shock. CCT eligibles may also diversify risk during shocks, leading to an increase in lending to collective funds in the informal insurance system. In contrast, program participation has a crowding-out effect on bank borrowing, as evidenced by the negative and significant decrease in bank borrowing in column 5 during the income shock. Therefore, during covariate shocks, the program eligibles engage with the informal system through positive borrowing and lending, thus keeping the informal system thriving. However, the CCT program, through eligibles, crowds out formal bank borrowing during shocks and attracts informal moneylenders, indicating that the eligibles prefer the informal insurance system and moneylenders over bank borrowing in times of emergencies brought about by natural disasters. This rests on the assumption that sharing norms are strong, resulting in an increase in support of ineligibles to the informal network.

Panel B of Table 4 shows the regression results for ineligible household samples. Performing the same Tobit regression and set of controls, the results show that ineligible households in the treated areas significantly decrease their borrowing from friends during shocks. This may be partly because the ineligibles' confidence about their ability to repay loans is low due to uncertainty in their economic condition during shocks. This low confidence leads them to reluctantly borrow more money from the informal insurance system. However, according to IPW estimates, among the above PMT group, the program significantly increases informal lending during covariate shocks. It appears that the program enhances informal transactions driven by lending from the "near-poor" households. This means that ineligibles trust CCT eligibles by lending money in the informal network because eligibles receive benefits from CCT. Since it is unlikely that eligibles, who are typically less wealthy, are lending money to relatively more wealthy ineligibles, the result suggests that eligibles increased borrowing from ineligibles.

4.3. Estimates on sub-groups analysis

This section analyzes the imbalance found in the village-level shock index of natural disasters in Table 1. To investigate whether pre-treatment imbalance affects our results, we examine the top three natural disasters reported by the barangay captain: flood, drought, and earthquake. Earthquake was reported as the highest among the natural disasters with more than 60 percent on average, followed by flood with almost 60 percent, and drought with more than 40 percent. Among the three natural disasters, flood and drought show significant mean differences between treatment and control groups, while earthquake remains balanced between the two groups. This may suggest that treatment villages are more prone to flooding and drought than control villages, although it was not explicitly mentioned in the implementation procedure. Given that possibility, we further examine if the villages that are more prone to natural disasters have stronger informal safety nets and social capital.

A natural disaster index was created covering the top three natural disasters mentioned above. The measurement represents an index assigned to each village ranging from zero to three, with zero being the lowest and three being the highest. Next, a natural disaster intensity is created based on the natural disaster index, which is equal to one if there are two or more natural disasters occurring in the village and zero otherwise. Separating the villages into two subgroups describing high and low intensities of climate risk is a more sensible approach and straightforward to interpret. Table 1 shows balance in means in treatment and control groups for the natural disaster intensity variable for the below and above PMT groups. This means that the two groups are now balanced and comparable, allowing us to test the hypothesis that CCT mitigates climatic risks and affects informal safety nets. It is expected that highly intensive natural disasters may damage infrastructure hugely and broadly affect a large number of residents in the village, making them incapable of helping their neighbours.

The result of the sub-group analysis of high and low natural disaster intensities in Table 5 suggests that CCT mitigates climatic risks and affects informal safety nets in villages with low intensities of climate risk. Under the assumption that CCT could mitigate climate risks and affect informal insurance in local communities where the financial system is operating and coordination and monitoring are possible, the results in Table 5 confirm it. The result from Panel A and C describing high-intensity natural disasters measured by two or more natural disasters suggests that CCT may not adequately mitigate climatic risk. This is especially true when the natural disaster is severe enough to devastate the local community by damaging infrastructure, making CCT challenging to implement in the locality. When there is no shock, CCT increases formal borrowing in intensively high natural disaster villages, as shown by positive and significant bank borrowing in Panel A. This suggests that the financial system may not operate well in intensively high climatic risk areas.

TABLE 5. Sub-group analysis: villages with high and low natural disaster intensity

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	Borrowings from bank
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Eligibles in high natural disaster intensity villages					
Program assignment (w/out covariate shock)	0.22 (0.28)	0.08 (0.14)	-0.19 (0.25)	-0.23 (0.27)	0.39* (0.22)
Covariate shock (proxied by harvest failure)	-0.94** (0.46)	-0.04 (0.14)	-0.66 (0.42)	0.30 (0.46)	0.64* (0.33)
Program assignment X Covariate shock	1.01 (0.82)	0.07 (0.35)	0.38 (0.80)	-0.60 (0.54)	-1.39** (0.56)
Constant	-0.64 (1.20)	0.12 (0.45)	-1.80* (0.99)	-1.19 (0.76)	-1.97** (0.93)
Observations	511	511	511	511	511
Pseudo R^2	0.0837	0.0129	0.156	0.0410	0.0597
Panel B: Eligibles in low natural disaster intensity villages					
Program assignment (w/out covariate shock)	0.94** (0.44)	-0.03 (0.09)	-0.11 (0.32)	-1.04*** (0.34)	0.34 (0.22)
Covariate shock (proxied by harvest failure)	-0.26 (0.70)	-0.51 (0.34)	-0.81 (0.81)	-0.89 (0.57)	-0.22 (0.60)
Program assignment X Covariate shock	0.43 (1.04)	0.48 (0.33)	1.75* (0.93)	2.05** (0.80)	-0.70 (0.56)
Constant	-4.20*** (1.17)	0.35 (0.69)	-4.07*** (1.28)	-0.10 (1.07)	-1.70** (0.78)
Observations	452	452	452	452	452
Pseudo R^2	0.0836	0.0310	0.150	0.0378	0.0317
Panel C: Ineligibles in high natural disaster intensity villages					
Program assignment (w/out covariate shock)	-1.57* (0.86)	-0.55 (0.60)	-2.03** (0.82)	-1.80** (0.77)	1.34 (0.84)
Covariate shock (proxied by harvest failure)	-0.76 (1.41)	0.78 (1.58)	0.29 (1.71)	-0.48 (2.39)	-0.57 (1.07)
Program assignment X Covariate shock	1.35 (1.74)	0.08 (1.60)	-2.25 (2.07)	-1.15 (2.57)	1.78 (1.39)

TABLE 5. Sub-group analysis (continued)

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	from bank
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Constant	1.52 (2.90)	2.30* (1.33)	0.05 (1.84)	0.74 (2.25)	-1.36 (1.87)
Observations	89	89	89	89	89
Pseudo R^2	0.0598	0.0525	0.157	0.0717	0.149
Panel D: Ineligibles in low natural disaster intensity villages					
Program assignment (w/out covariate shock	1.46 (1.02)	0.69 (0.58)	-0.33 (0.97)	-0.66 (0.74)	1.03 (0.92)
Covariate shock (proxied by harvest failure)	-3.36 (2.01)	0.27 (0.98)	-3.71* (2.05)	-3.81* (1.93)	0.07 (2.52)
Program assignment X Covariate shock	4.24** (1.64)	2.56*** (0.95)	4.10** (1.79)	4.46*** (1.58)	-1.45 (2.29)
Constant	6.38 (3.87)	3.48 (2.27)	1.09 (2.33)	-0.00 (1.60)	-3.11 (2.61)
Observations	71	71	71	71	71
Pseudo R^2	0.0934	0.110	0.123	0.0597	0.0984

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost, and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations. $p<0.01$; $^{**}p<0.05$; $^{***}p<0.001$

5. Conclusion

This study employed a randomized experimental design to assess the impact of the CCT program, focusing on its risk-mitigating and spillover effects on informal insurance systems in the Philippines, where poor households frequently contend with income shocks from natural disasters. An ITT analysis was utilized to estimate the model with the program assignment.

The findings reveal the risk-mitigating effects of CCT on eligible households' medical expenses during covariate shocks such as harvest failure. The CCT program led to eligibles significantly increasing their borrowing in the informal risk-sharing system during shocks, opting for informal support over formal banking or microfinance options.

Furthermore, CCT potentially strengthened the informal insurance system, as ineligibles in the treatment areas increased their lending support in response to shocks. This can be attributed to CCT improving the creditworthiness of eligibles who receive regular cash transfers, thus fostering positive reputations within the informal network. The decrease in ineligibles' borrowings from the informal network may also suggest a positive spillover effect of CCT to informal insurance, as CCT's eligible households share the values of saving and mutual support with ineligibles, thereby avoiding overexploitation of resources within the informal insurance system. This is because the CCT program, through the monetary and other benefits, alters the behaviour of eligibles, creating a broad impact on the entire informal network, which in turn affects the ineligibles, given the high social capital within informal networks where members share common goals and values. Overall, this study sheds light on the unintended consequences of CCT programs in the Philippines and contributes to related studies on CCTs in Africa and Latin America.

However, the study has limitations. It only analysed the risk-mitigating effects of CCT for covariate shocks proxied by harvest failure, while informal risk-sharing arrangements often prove more effective during idiosyncratic shocks such as illnesses, death, and unemployment. Unfortunately, examining the impact of idiosyncratic shocks in the study model raises endogeneity issues. The bias is introduced by other factors that influence the individual's decision to participate in informal risk-sharing arrangements. For example, individuals with poor health or those who face high mortality risk are more likely to participate in informal risk-sharing arrangements, but healthy individuals are less likely to do so. Therefore, the decision to join or leave a risk-sharing network is not an arbitrary or chance event but is based on one's health status. The same is true for unemployment, where the decision to participate in informal insurance may be influenced by employment conditions, such as job loss, rather than a random choice. Therefore, instrumental variables are required to control for endogeneity; however, they are presently unavailable. Future studies should aim to address these limitations by identifying detailed channels through which public transfers affect existing informal arrangements, using instrumental variables to control for endogeneity.

While our analysis focuses on covariate shocks to shed light on the limitations of informal insurance mechanisms under widespread risk, we recognize that most households in reality are simultaneously exposed to both idiosyncratic and covariate shocks. Moreover, the structure and strength of informal insurance networks—as well as households' exposure to risk—vary considerably across geographic contexts, which may limit the generalizability of our findings. These differences underscore the importance of future research that explores how informal networks operate under more complex and heterogeneous shock environments. Our findings, which highlight the inherent constraints of informal risk-sharing in the face of covariate shocks, provide a conservative benchmark for evaluating the potential complementarity between informal arrangements and formal policy interventions.

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Appendix A. Inverse Probability Weighting (IPW) estimation and the non-attrition probit model

This section explains the procedure for estimating Equations 2 and 3 using IPW to address the loss of observations caused by missing data in the covariates $\boldsymbol{X}_{ij}$. First, we used the probit model for Equations 1 and 2 to predict the outcomes using samples without missing data. We then generated the inverse of the probability weights for each individual. The probability of non-attrition is given by:

$$P(T = 1 | \boldsymbol{X}_{ij})$$

Next, we re-estimated the models using the generated inverse probability weights. Table A1 shows the estimates for the non-attrition probit model, covering the samples from the covariates in Models 2 and 3 with non-missing values.

TABLE A.1. Estimation results for the non-attrition probit model

Variables	Non-attrition = 1
Age	-0.01* (0.01)
Gender (1=Female)	-1.12*** (0.14)
Married (1=Yes)	0.20 (0.19)
Nature of employment (1=Permanent)	1.64*** (0.17)
Household size	0.02 (0.03)
Durable Asset Index	-0.02 (0.04)
Has a loan (1=Yes)	0.23* (0.13)
Has a bank account (1=Yes)	0.09 (0.26)
Barangay population	0.00 (0.00)
Insurance index (health, life, housing, and other social insurance)	0.17 (0.10)
Health facility index (rural health center, clinic, hospital, pharmacy etc.)	-0.03 (0.05)
Municipality 2	0.02 (0.30)
Municipality 3	0.44 (0.29)
Municipality 4	0.27 (0.29)

TABLE A.1. Estimation results for the non-attrition probit model (continued)

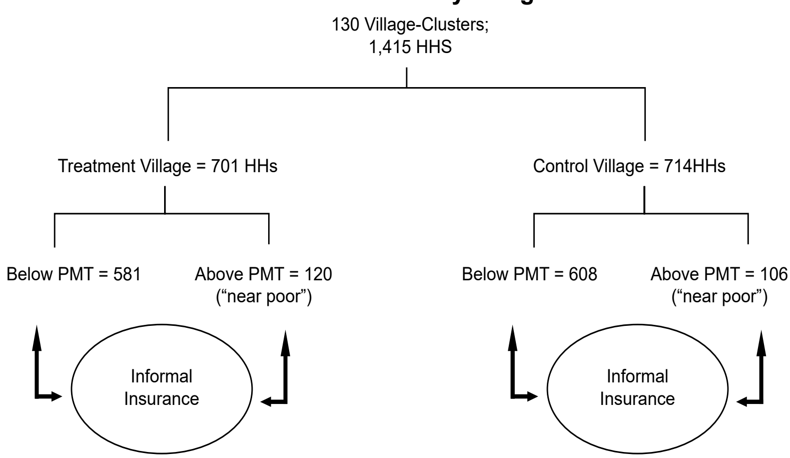
Variables	Non-attrition = 1
Municipality 5	0.47 (0.44)
Municipality 6	0.31 (0.40)
Municipality 7	0.06 (0.32)
Municipality 8	-0.18 (0.32)
Constant	0.65 (0.50)
Observations	1,124

Reference dummy for Municipality is Municipality 1. **p*<.01; ***p*<.05; ****p*<.001

Appendix B. Study design

Figure A.1 illustrates the study design, highlighting the randomization of treatment and control groups from the village clusters across the country. The study includes 1,415 households from 130 village clusters, with 701 households in treatment villages and 714 households in control villages. In the treatment villages, 581 households have PMT scores below the poverty threshold, and 120 households have PMT scores above the poverty threshold. In the control villages, 608 households have PMT scores below the poverty threshold, and 106 households have PMT scores above the poverty threshold. Households with PMT scores above the threshold are considered "near poor" because their scores are just above the poverty threshold.

FIGURE A.1. Study design



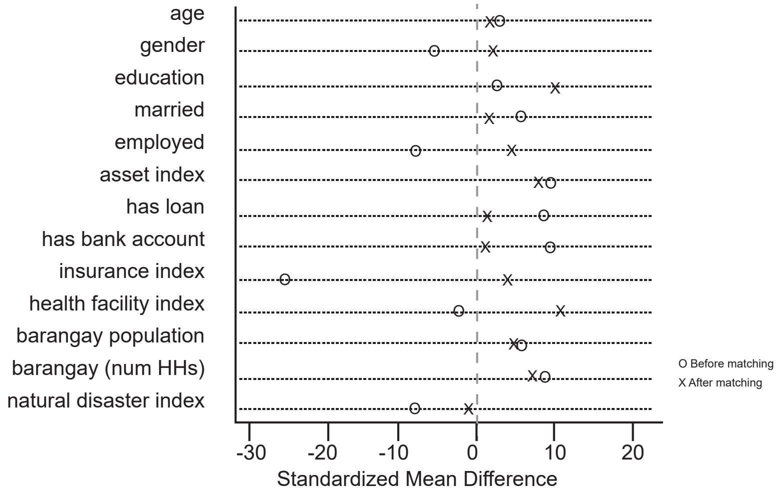
Appendix C. List of variables and their definitions

Variables	Definition
Age	Age of the household head
Gender	Gender of the household head
Educational attainment	Educational attainment of the household head
Marital status	Household head that is married
Nature of employment	Household head that is permanently employed
Household size	The number of family members in a household
Durable asset index	Assets owned by the household which covers the following: 1) Television set 2) VTR/VHS/VCD/DVD 3) Stereo / CD player 4) Refrigerator / freezer 5) Washing machine 6) Air conditioning 7) Living room or sala set 8) Dining set 9) Car or jeepney 10) Telephone or mobile phone 11) Personal computer 12) Microwave oven 13) Motorcycle
Has an outstanding loan	Currently has an outstanding loan
Has bank account	At least one of the household members has opened a bank account and it is active or usable.
Insurance index	At least one of the household members has any of the following social insurance programs: 1) Government Service Insurance System (GSIS) 2) Social Security System 3) Philippine Health Insurance Corporation (PhilHealth) 4) Health insurance from private company 5) Life insurance
Harvest failure	The household experienced harvest failure and financial instability in the past 12 months.
Per capita consumption	Household’s annual per capita consumption of all food and non-food items consumed, including purchases made in cash or on credit, gifts received, or items own-produced, over the past six months.
Per capita education expenditure	Household’s annual education expenditure per child, covering tuition fees, graduation fees, allowances, books, school supplies, etc. These expenditures represent actual disbursements made, whether paid in cash or on credit, or received as gifts, over the past six months.
Per capita medical expenditure	Household’s annual actual expenditures on medical care, including drugs & medicines, hospital room charges, medical and dental charges, other medical goods & supplies, herbal medicines, etc. These expenditures encompass payments made whether in cash or on credit, or received as gifts, over the past six months.

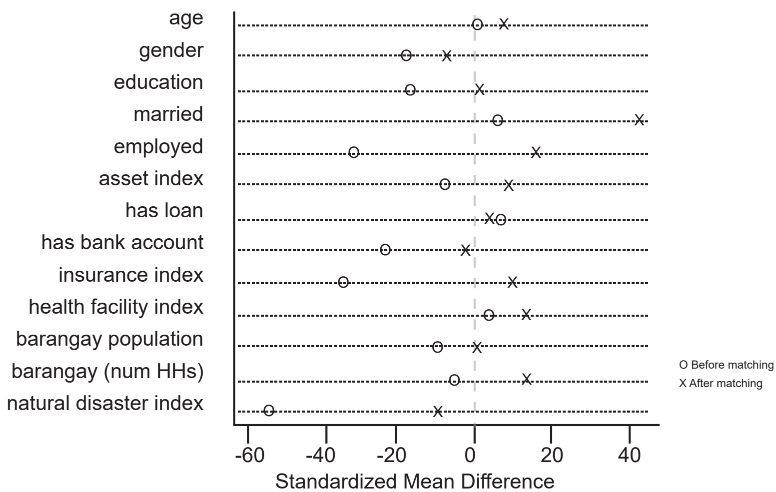
Per capita of dairy consumption	Household's annual per capita consumption of dairy products, including eggs, milk, ice cream, butter, cheese, fresh eggs, salted eggs, and duck eggs, consumed from purchases made whether in cash or on credit, or received as gifts, or self-produced during the past six months.
Per capita of meat consumption	Household's annual per capita consumption of meat and meat preparations, such as fresh chicken, fresh beef, fresh pork, corned beef, goat's meat, luncheon meat, meat loaf, vienna sausage, longanisa, chorizo, hotdog, tocino, tapa, etc., consumed from purchases made whether in cash or on credit, or received as gifts, or self-produced during the past six months.
Per capita of alcohol consumption	Household’s annual per capita consumption of alcoholic beverages, such as beer, tuba, basi, lambanog, brandy, whisky, rum, etc., consumed from purchases made whether in cash or on credit, or received as gifts, or self-produced during the past six months.
Total borrowings and lending to friends and relatives	The total amount of money currently borrowed and lent from friends and relatives
Borrowings to friends and relatives	The amount of money currently borrowed from friends and relatives
Borrowings to moneylender	The amount of money currently borrowed from moneylenders
Lending to friends and relatives	The amount of money lent to friends and relatives
Bank borrowings	The amount of money borrowed from banks.
Barangay population	The population of the barangay or village, as reported by the barangay or village captain.
Households in barangay	The number of households in the barangay or village, as reported by the barangay or village captain.
Health facility index	Whether flooding occurred in the barangay or village (which includes barangay health station, rural health unit / center, traditional birth attendant or “hilot,” private clinic, government hospital, private hospital, barangay pharmacy, private pharmacy). This information is provided by the barangay or village captain.
Flood	Whether flooding occurred in the barangay or village in the last five years that caused widespread disaster to most residents. This information is provided by the barangay or village captain.
Earthquake	Whether an earthquake occurred in the barangay or village in the last five years that caused widespread disaster to most residents. This information is provided by the barangay or village captain.
Drought	Whether a drought occurred in the barangay or village in the last five years that caused widespread disaster to most residents. This information is provided by the barangay or village captain.
Natural disaster intensity	Classified into two categories: high and low intensities. High intensity means that the barangay or village experiences two or more natural disasters, including floods, droughts, or earthquakes. Low intensity means that the barangay or village experiences not more than one natural disaster, whether floods, droughts, or earthquakes.

Appendix D.

Love Plot: Covariate Balance (Below PMT)



Love Plot: Covariate Balance (Above PMT)



PRE The Philippine Review of Economics
62(1):112-126. DOI:10.37907/5ERP5202J

Pulling up from the depths of poverty: Do the Pantawid Pamilya cash transfers to the poor reduce their consumption expenditure shortfalls?

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With its emphasis on incentivizing beneficiary households to invest in the health and education of their children, the Philippines' Pantawid Pamilyang Pilipino Program (4Ps) is expected to reduce future poverty. Yet, the cash transfers provided under the program have impacts on the household's current income and consumption, and therefore, on contemporaneous poverty status. While the transfers may be inadequate to lift the poor out of poverty, these could pull them up from the depths of poverty. Using a panel dataset, we estimated the elasticity of the region-level income gap and poverty gap, both based on per capita consumption expenditures, with respect to 4Ps indicators, controlling for other factors. In general, the poverty gap is not responsive to 4Ps indicators. In contrast, the income gap is sensitive to changes in the total 4Ps cash transfers, with the effect moderated by the poverty incidence in the region. The policy implication is that, among the 4Ps beneficiaries, the poor could be granted greater cash transfers to pull them up from the depths of destitution.

JEL classification: D12, H53, I38
Key words: conditional cash transfers, household income, household consumption expenditures, poverty gap, income gap, Philippines

1. Introduction

As a conditional cash transfer (CCT) program, the Philippines' Pantawid Pamilyang Pilipino Program (4Ps) is expected to reduce future poverty. By incentivizing beneficiary households to invest in the human capital of their children and those still in the wombs of their mothers, the program envisions these children to become healthy and productive adults with better living and

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economic conditions than their parents. Indeed, many evaluation studies report that Pantawid Pamilya beneficiary households, relative to non-beneficiaries, are more likely to send their children to school, bring them to clinics for health checkups and immunization, or ensure they have better nutritional status (see, for example, Tabuga et al. [2013]; Orbeta et al. [2021]).

However, CCT programs may also affect current household welfare through potential adverse effects on the labor force participation of adult members or consumption behavior. Here, the available evidence concerning the 4Ps is mixed. Orbeta and Paqueo [2016] report that the 4Ps does not disincentivize work or promote vices. According to Tutor [2014], the 4Ps generally has no effect on total consumption or consumption choices. While Quimbo et al. [2021] also report the 4Ps to have no effect on the consumption of both the poor and non-poor beneficiaries, the program is found to be associated with a lower incidence of child labor among the poor beneficiaries and with reductions in wages and salaries of the non-poor beneficiaries. Yet, the Pantawid Pamilya led to reductions in the per capita expenditures of household beneficiaries in urban areas [Capulong and Cuevas 2024]. The evidence from other countries is likewise varied. Indonesia's own CCT Program, the Program Keluarga Harapan has improved individual consumption, although the effect is nil for the poorest among the beneficiaries [Hadna and Askar 2022]. Since Mexico's Progressa Programme is found to have no effect on the labor or leisure outcomes of adults, Skoufias and Di Maro [2008] averred that the cash transfers were a net addition to the incomes of the beneficiary households.

To the extent that CCT impacts current household income or consumption, it also affects present poverty status. While the cash transfers provided to most beneficiary households may not be enough to lift them out of poverty, the amount could move them closer to meeting their basic needs. Put differently, the cash transfers to the poor move their incomes closer to the poverty line. As it were, the CCT pulls them up from the depths of poverty. Indeed, there is some evidence that CCT has reduced the poverty gap, which is a measure of the depth of poverty. In their review of the various CCT programs in Latin America, Fiszbein et al. [2009] report that the programs had positive and significant effects on the per capita consumption of the median households, and have reduced poverty gaps in Colombia, Honduras, Mexico, and Nicaragua. Skoufias and Di Maro [2008] also found the poverty gap in Mexico to have been reduced by the Progressa Programme. In a sample of households in Camarines Sur Province, the poverty gap in a locality covered by the 4Ps is found lower by 0.08 than in the comparison locality [Onsay, Arapoc, and Rabajante 2015].

This paper contributes to the debate by examining anew the impact of the 4Ps on the depths of poverty across regions in the Philippines. Using a panel dataset, we estimated the elasticity of the income gap and poverty gap, both based on per capita consumption expenditures, with respect to 4Ps indicators, controlling for other factors. In general, the poverty gap is not responsive to 4Ps indicators. In contrast, the income gap is sensitive to changes in the total 4Ps cash transfers, with the effect moderated by the poverty incidence in the region. By reducing the required consumption expenditures to meet their basic needs (as reflected in the poverty threshold), the Pantawid Pamilya cash transfers pull the poor up from the depths of destitution.

The rest of the paper is organized as follows: a short overview of the 4Ps is provided in Section 2, then followed by a description of the data and methods used (Section 3). Section 4 presents the results. The last section concludes the paper.

2. Overview of the Pantawid Pamilyang Pilipino Program[1]

Patterned after the highly regarded conditional cash transfer programs implemented in Latin America, the Philippines' own became a regular program of the Department of Social Work and Development with the signing in 2019 of the Republic Act No. 11310 (*An Act Institutionalizing the Pantawid Pamilyang Pilipino Program* (4Ps)). First introduced on a pilot basis in 2007, the Pantawid Pamilya program (also called 4Ps) has since then expanded its population coverage and amounts of cash transfers provided (see, for example, Acosta and Velarde [2015]). Under the so-called 4Ps Act, the program is further secured with an annual budget appropriation.

Identified through a proxy means test (called the National Household Targeting System for Poverty Reduction or *Listahanan*), the eligible households are selected if they reside in the poorest municipalities, live in economic conditions (indicated by their predicted incomes) below or equal to the provincial poverty threshold, have children 0-18 years old or a pregnant woman at the time of enumeration, and agree to comply with program conditionalities. The program covers both poor and near-poor households. A beneficiary household can expect to receive a cash transfer consisting of a health grant of ₱750 per month, an education grant of ₱300 per child in elementary school, ₱500 per child in junior high school, and ₱700 per child in senior high school for up to three children per beneficiary household and ten months per academic year.

To avail themselves of the cash transfers, beneficiaries are expected to have their school-age children enrolled, regularly attend classes, and routinely take their children aged zero to five to clinics for immunization, health check-ups, and nutrition services, among others. Additionally, a pregnant household member is

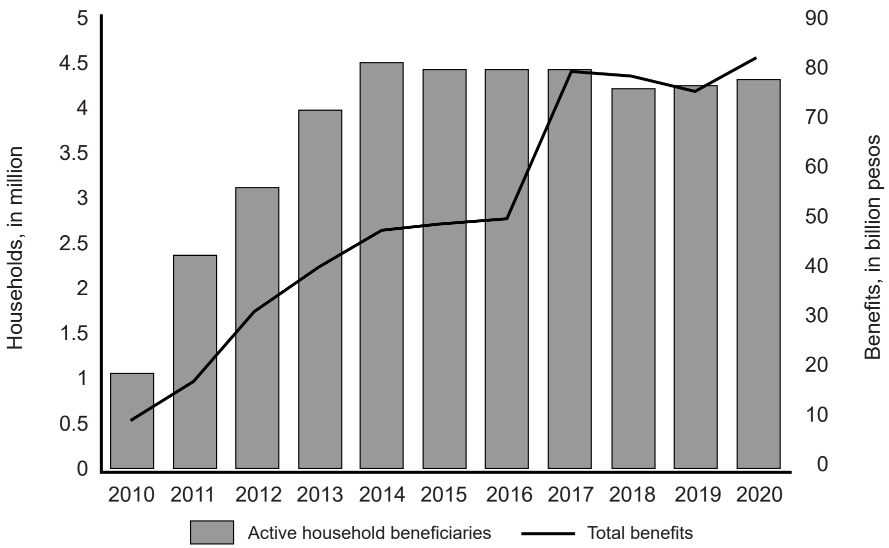
[1] Much of the information here is drawn from the DSWD's 4Ps website (https://www.dswd.gov.ph/pantawid-pamilyang-pilipino-program-4ps/) accessed on May 1, 2025. Note that the some of the eligibility requirements and benefit entitlements have evolved through the years. Previously, for example, one of the requirements is for a household to have children aged 0-15 years, instead of the current age range of 0-18 years. Previously, the education grant was ₱500 per child, regardless of whether the child is in elementary or high school. Currently, the education grant varies by education level of the child beneficiary. For more of the early program features, see, for example, Fernandez and Olfindo [2011].

required to seek pre-natal consultations, deliver her baby in a health facility, and avail herself of post-partum care services. One responsible household member is also expected to attend monthly Family Development Sessions.

By design, the 4Ps addresses both future and present poverty conditions. By putting a premium on the health and education of children, the program helps ensure that once these young household members become adults, they will not end up poor like their parents. Meanwhile, monetary support can help the beneficiaries meet their current basic needs, even if the amount is not enough to lift them out of their present poverty status.

To get a sense of how the 4Ps could pull its beneficiaries up from the depths of poverty, Figure 1 shows the growth in the number of active beneficiary households and the total amount of benefits extended to them from 2010 to 2020 (July). From slightly over a million in 2010, the number of active beneficiary households reached nearly four million in 2013. In the following year, the highest coverage at nearly 4.5 million households was reached. Still, annual coverage remained upwards of four million households since then. The increase in total benefits is equally striking. From about ₱10 billion in 2010, the total benefits rose to nearly ₱50 billion in 2016, and then to ₱79 billion in 2017. While there was no significant change in household coverage between 2016 and 2017, the big increase in benefits between those years was the rice allowance additionally granted to all beneficiaries. The rice grant continued for the next three years.

FIGURE 1. Active 4Ps beneficiary households and total benefits, 2010-2020*

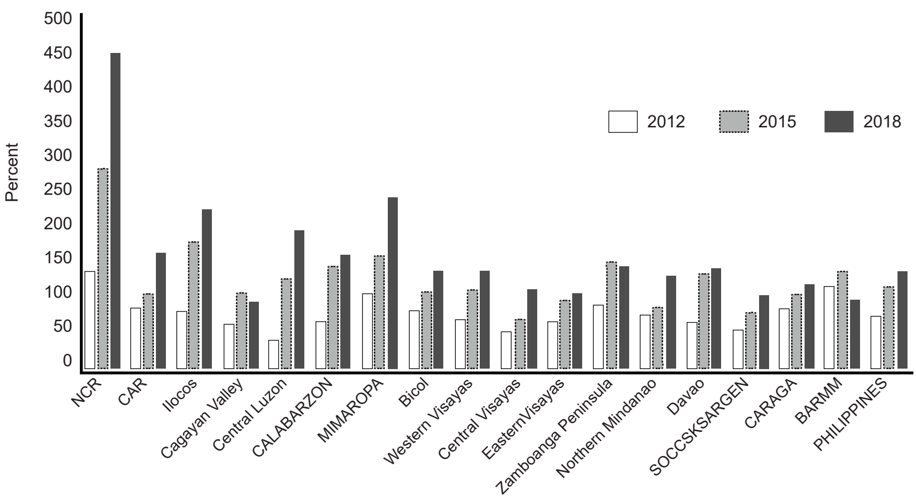


*As of July 2020.
Source: Department of Social Work and Development.

Since the 4Ps also covers near-poor households, it is important to know if its total coverage is more or less than the official number of poor households, which constitute its primary target beneficiaries. As shown in Figure 2, in 2012 the number of active beneficiary households was less than 100 percent of the total number of poor households in 14 regions. The proportion is over 100 percent only in the National Capital Region, MIMAROPA, and the Bangsamoro Autonomous Region of Muslim Mindanao (formerly the Autonomous Region of Muslim Mindanao). By 2015, the proportion remained below 100 percent only in four regions (Central Visayas, Eastern Visayas, Northern Mindanao, SOCCSKSARGEN). By 2018, all regions save two (Cagayan Valley, BARMM) exceeded 100 percent. Three regions attained a total 4Ps coverage that was even double their number of poor households.[2]

Notwithstanding the possible leakages in the identification of eligible beneficiaries, the growth in the 4Ps's coverage across regions and in its total cash assistance suggests that most, if not all, of the poor must have benefitted under the program. We examine if the benefits moved the poor closer to attaining their basic needs, as reflected in the poverty threshold.

FIGURE 2. Active 4Ps beneficiary households as a percentage of poor households, by region and selected years



Notes: The number of active 4Ps beneficiary households, which includes the poor and near-poor households determined under the National Household Targeting System, are obtained from the Department of Social Work and Development. The number of poor households (based on headcount ratio) is obtained from the Philippine Statistics Authority.
Source: Author's calculation.

[2] Since the number of 4Ps beneficiary households remained relatively constant from 2015 onwards compared to the trends before (Figure 1) and that the program has increasingly covered more than 100 percent of the poor households since 2012 (Figure 2), this can be explained by the fact that the economy experienced a growth spell and poverty declined continuously during the 2012 to 2018 period (Clarete, Esguerra, and Hill [2018]; Capuno [2022b]).

3. Data and empirical methods

3.1. Data sources

We assembled a panel dataset comprising various indicators for each of the country's 17 regions for the years 2012, 2015, and 2018. We selected these years to match the official poverty and inequality indicators derived from the last three rounds of the Family Income and Expenditures Survey (FIES) conducted before the COVID-19 pandemic. The FIES is designed to collect detailed household-level information on income and expenditures, as well as their members' socioeconomic and demographic profiles. The household samples per round are representative both at the national and regional levels. There were 40,171 household samples in 2012, 41,544 in 2015, and 147,717 in 2018. We obtained the public use files of the FIES from the Philippine Statistics Authority (PSA) to calculate the depths of poverty based on household consumption expenditures per capita.

From the PSA's website and its Philippine Statistical Yearbook, we also obtained data on population, Consumer Price Index (CPI), Gross Regional Domestic Product (GRDP), poverty thresholds, official estimates of headcount ratio, number of poor households and Gini ratios, and unemployment rates. We applied the regional poverty thresholds in computing the consumption-based estimates of the income gap and poverty gap (formally defined below). These estimates are derived using ADePT 6, a free software platform obtained from the World Bank. Meanwhile, we acquired information on the number of active 4Ps beneficiary households and the total cash transfers per region from the DSWD.

3.2. Measures of depths of poverty

To characterize the depths of poverty in the population, we use the poverty gap and income gap measures. Unlike the official estimates based on per capita income, we computed these measures here using per capita consumption expenditures (PCE), which is a better measure of welfare (Balisacan [2000;2003]; Ravallion [2016]). Following the exposition in Forster et al. [2013], let the PCE distribution in society with N population be denoted by the vector $y = (y_1, y_2, y_3, \ldots, y_N)$, where y_i is the PCE of person i. Assume further that the individuals are arranged from lowest to highest PCE such that $y_1 \leq y_2 \leq y_3 \leq \ldots \leq y_N$. Let z denote the poverty threshold, such that any individual whose PCE falls below the threshold is considered poor. If, instead, his or her PCE is at least equal to z, then he or she is not poor. Let q denote the number of poor individuals in the society, and their proportion in the population is called the headcount ratio, $H = q/N$.

For person i, his or her consumption expenditure shortfall as a proportion of the poverty threshold is $(z - y_i)/z$. Since some individuals are not poor, they do not have positive consumption expenditure shortfalls, as defined. For a nonpoor individual, let his or her consumption expenditure shortfall be normalized to zero (i.e., his or her consumption expenditure is set equal to z). The income gap (IG) is defined as the average consumption expenditure shortfall among the poor, as given by:

$$IG = \frac{1}{q}\sum_{i=1}^{q}\left(\frac{z - y_i}{z}\right).$$

Meanwhile, the poverty gap (PG) is defined as the average normalized consumption expenditure shortfall for the population, that is:

$$PG = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{z - y_i^*}{z}\right),$$

where $y_i^* = y_i$ if person i is poor, and $y_i^* = z$ if person i is nonpoor. The PG can also be expressed as:

$$PG = \left[\frac{N-q}{N} \times 0\right] + \left[\frac{q}{N} \times \frac{1}{q}\Sigma_{i=1}^{q}\left(\frac{z-y_i}{z}\right)\right],$$

where the first bracketed term on the right side is the average normalized shortfall among the nonpoor, while the second bracketed term is simply the product of H and IG. This means that anything that will increase (decrease) H or IG will tend to increase (decrease) PG as well. It is also evident from the definitions of the IG and PG that both will tend to decrease with a rise in the consumption expenditures of the poor, ceteris paribus. To the extent that cash transfers will lead to higher consumption spending, the 4Ps is thus expected to pull up its beneficiary households from the depths of poverty.

3.3. Estimating equations

We assess the efficacy of the 4Ps in pulling up the beneficiary households from the depths of poverty by estimating a regression equation of the following form:

$$P_{it} = \alpha_i + \gamma X_{it} + \boldsymbol{Z}'_{it}\boldsymbol{\theta} + \boldsymbol{\delta_t} + \varepsilon_{it}\,,$$

where P_{it} is the indicator of the depths of poverty in the ith region in year t, X is a 4Ps indicator, $\boldsymbol{Z}$ is a vector of control variables, $\boldsymbol{\delta}_t$ is a vector year dummy variables, α_i is region-specific intercept (also meant to capture region-specific fixed effects), γ and $\boldsymbol{\theta}$ are regression coefficients to be estimated, and ε_{it} is the error term. The equation is estimated using the fixed-effects panel data regression method [Cameron and Trivedi 2005; Wooldridge 2010].

We try several model specifications. In models where the IG is the dependent variable, the headcount ratio is included among the regressors and sometimes interacted as well with the 4Ps indicators. In models where the PG is the dependent variable, the headcount ratio is excluded, since the PG formula already incorporates the headcount ratio. We introduced alternately two sets of 4Ps indicators, namely: the average annual 4Ps cash transfers per beneficiary household, and the annual cash transfers and the number of beneficiary households.

3.4. Regression variables

Table 1 lists the regression variables, their definitions, and summary statistics. All variables in the list are measured for each of the country's 17 regions and the years 2012, 2015, and 2018, yielding a balanced panel dataset with a total of 51 observations. Used as the main dependent variables, PG1 and IG1 are the PCE-based estimates of the poverty gap and income gap, respectively. The 4Ps indicators are average 4Ps cash transfers, 4Ps cash transfers, and 4Ps households. Note that the first 4Ps indicator, by definition, is equal to the ratio of the second to the third 4Ps indicator. Hence, either only the first 4Ps indicator or only the next two are used as regressors at a time.

The rest of the variables serve as controls. Both the Headcount ratio and the Gini ratio are official estimates (income-based). Since the Headcount ratio is already a part of PG, it is never used as a control when the dependent variable is PG1. When IG1 is the dependent variable, the Headcount ratio is introduced with or without interaction with the 4Ps indicators. The interaction serves to capture the idea that the efficacy of the 4Ps benefits may vary with poverty incidence in the region. Also serving as controls are the Gini ratio, which accounts for the extent of income inequality, and gross regional domestic product per capita, which is used to capture the overall level of economic activity. Finally, the employment rate serves to capture the extent to which the people, including the poor, partake of the job opportunities in the region.

To capture time-specific factors that affect all regions simultaneously, dummy variables for the years 2015 and 2018 are constructed. The default year is 2012. Region-specific factors are implicitly accounted for in the regression estimation. Except for Year 2015 and Year 2018, all regression variables are transformed into natural logarithms. Hence, their estimated coefficients are interpreted as elasticities. Our elasticity estimates are derived using STATA 18.

TABLE 1. Variable definitions and summary statistics

Variable	Definition*	Mean	Standard deviation	Min.	Max.
PG1	Poverty gap (own, based on consumption expenditures)	1.977	0.883	-0.711	3.287
IG1	Income gap (own, based on consumption expenditures)	3.194	0.215	2.653	3.511
Average 4Ps cash transfers	Annual cash transfers per 4Ps beneficiary household	9.559	0.215	2.653	3.511

TABLE 1. Variable definitions and summary statistics (continued)

Variable	Definition*	Mean	Standard deviation	Min.	Max.
4Ps cash transfers	Annual 4Ps cash transfers	21.796	0.562	20.312	22.715
4Ps households	Number of active 4Ps beneficiary households	12.238	0.493	10.924	12.992
Headcount ratio	Headcount ratio	3.091	0.710	0.788	4.124
Gini ratio	Gini ratio	3.732	0.119	3.332	3.880
Gross regional domestic product per capita	Gross regional domestic product per capita	11.622	0.450	10.686	12.977
Employment rate	Employment rate	4.549	0.019	4.493	4.577
Year 2015	=1 if year is 2015, 0 otherwise	0.333	0.476	0	1
Year 2018	=1 if year is 2018, 0 otherwise	0.333	0.476	0	1

*Except for Year 2015 and Year 2018, all variables are in natural logarithm. The average 4Ps cash transfers, 4Ps cash transfers, and the gross regional domestic product per capita are expressed in 2012 prices.

4. Results

Table 2 presents the regression estimates. As shown in columns [1] and [2], the elasticity of PG1 with respect to average 4Ps cash transfer and 4Ps cash transfers are 0.244 and 0.252, respectively. While both estimated elasticities do not have the expected negative sign, neither is statistically significant. On the other hand, 4Ps households is negative, though also insignificant.

With IG1 as the dependent variable, we also note in columns [3] – [6] that none of the 4Ps indicators is significant. In column [7], where the average 4Ps cash transfer is interacted with the headcount ratio, its elasticity estimate now has the expected negative sign. However, it is statistically insignificant. Finally, in column [8], 4Ps cash transfers is negative (-0.319) and highly significant ($p<0.01$). Unlike in all other cases, 4Ps households is now positive, though still insignificant.

As for the control variables, gross regional domestic product per capita is consistently negative across models, and even significant at the ten-percent level but only when the dependent variable is IG1 and the Headcount ratio is not included or included without interaction (in columns [3] – [6]). The Headcount ratio is a positive and significant correlate of IG1 (in columns [4] – [7]). Employment rate is insignificant in all models. In column [8], both Year 2015 and Year 2018 are positive (at 0.157 and 0.349, respectively) and highly significant ($p < 0.01$).

TABLE 2. Estimates of the elasticity of the poverty gap and income gap with respect to Pantawid Pamilyang Pilipino Program (4Ps) benefits

Explanatory Variable	Dependent variable: PG1		Dependent variable: IG1					
					Without interaction with headcount ratio		With interaction with headcount ratio	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Average 4Ps cash transfers	0.244 (0.491)		0.101 (0.178)		0.065 (0.143)		-0.119 (0.097)	
4Ps cash transfers		0.252 (0.478)		0.089 (0.193)		0.052 (0.161)		-0.319*** (0.116)
4Ps households		-0.220 (0.587)		-0.135 (0.203)		-0.103 (0.162)		0.132 (0.097)
Headcount ratio					0.231** (0.097)	0.233** (0.097)	0.310*** (0.109)	0.281* (0.109)
Gini ratio	0.138 (0.551)	0.134 (0.558)	0.184 (0.339)	0.189 (0.346)	-0.011 (0.331)	-0.007 (0.338)	0.031 (0.358)	0.236 (0.374)
Gross regional domestic product per capita	-1.441 (1.249)	-1.425 (1.280)	-0.829* (0.499)	-0.852* (0.492)	-0.628* (0.343)	-0.653* (0.333)	-0.472 (0.351)	-0.548 (0.357)
Employment rate	-3.248 (3.202)	-3.633 (3.191)	0.193 (1.202)	0.739 (1.664)	1.114 (0.815)	1.725 (1.470)	-0.269 (1.203)	0.222 (1.401)
Year 2015	0.235 (0.212)	0.223 (0.232)	0.115 (0.083)	0.133 (0.085)	0.091 (0.056)	0.111** (0.055)	0.081 (0.053)	0.157*** (0.056)
Year 2018	0.061 (0.467)	0.047 (0.478)	0.088 (0.171)	0.107 (0.171)	0.123 (0.130)	0.145 (0.130)	0.197* (0.114)	0.349*** (0.124)

TABLE 2. Estimates of the elasticity of the poverty gap and income gap with respect to Pantawid Pamilyang Pilipino Program (4Ps) benefits (continued)

Explanatory Variable	Dependent variable: PG1		Dependent variable: IG1					
					Without interaction with headcount ratio		With interaction with headcount ratio	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Region fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Number of observations	51	51	51	51	51	51	51	51
Number of groups	17	17	17	17	17	17	17	17
R-squared (overall)	0.6174	0.6101	0.4491	0.4475	0.5974	0.5914	0.6615	0.6253
F-statistics	15.81	18.14	7.86	9.54	13.16	10.93	16.71	30.30
Prob > *F*	0.0000	0.0000	0.0005	0.0001	0.000	0.000	0.000	0.000
Mundlak specification tests (H_0: Covariates are uncorrelated with unobserved panel-level effects)								
χ^2 statistic	16.17	23.49	9.89	29.00	18.20	14.62	6.78	21.56
Prob> χ^2	0.0028	0.0003	0.0423	0.0000	0.0027	0.0234	0.3414	0.0058

Note: Panel data estimates of average marginal effects, with robust standard errors adjusted for regional clustering (in parenthesis). The dependent variable and all explanatory variables are in natural logarithms, except the dummy variables Year 2015 and Year 2018. The default year is 2012. In models [7] and [8], Average 4Ps cash transfers, 4Ps cash transfers, and 4Ps households are each interacted with the Headcount ratio. The poverty gap (PG1) and income gap (IG1) are based on per capita consumption expenditures, while the headcount ratio and Gini ratio are official estimates. ***$p<0.01$, **$p<0.05$, *$p<0.10$

The bottom row of Table 2 displays the results of the Mundlak specification tests. The test involves running the relevant model as a random-effects model and testing the null hypothesis that the covariates are not correlated with the unobserved region- or year-fixed effects. The results of the chi-squared tests indicate the null hypotheses can be rejected in nearly all cases save in column [7]. Overall, the results here validate our model specification to minimize the bias due to unobserved region-specific or year-specific factors.

5. Discussion and conclusion

While the anticipated impact of 4Ps in breaking the intergenerational transmission of poverty has yet to be established given that most of the children of its earliest beneficiary households are just starting to find their first jobs after finishing school, we contribute some findings here concerning its contemporaneous effect on household welfare. In particular, we examined the efficacy of the cash assistance in pulling up the destitutes from the depths of poverty.

Using a region-level panel dataset, we find that income gap is responsive to increases in the total amount of cash transfers, controlling for other actors. The estimated elasticity is -0.319 and highly significant. In contrast, poverty gap does not appear sensitive to the 4Ps cash transfers. As measures of depths of poverty, both the income gap and poverty gap incorporate in their formulas the difference between the poverty threshold and per capita consumption expenditures. That only the income gap appears sensitive to increases in 4Ps cash transfers could be explained by another finding: the poverty incidence moderates the effects of cash transfers on the income gap. That is, the same amount of cash transfers would reduce the income gap unequally between two regions with different poverty incidences.[3] Since the poverty gap already incorporates the poverty incidence, regressing the poverty gap against cash transfers interacted with the headcount ratio is tantamount to regressing a variable against itself. Another possible explanation is operational. Since the 4Ps covered both the poor and near-poor households (i.e., those just above the poverty threshold), the 4Ps cash transfers would show greater impact in reducing the consumption expenditure shortfall when the analysis is limited to the poor (as in the case of the income gap) than when it is extended to all of the population as in the case of the poverty gap, especially since the consumption expenditure of the near-poor 4Ps beneficiaries would be normalized to be equal to the threshold. In other words, the PG is insensitive to the transfers granted to those just above the threshold, no matter how many they are.

Since we used regionally aggregated data, there could be important or interesting individual household responses to the 4Ps cash assistance that are not

[3] Note that 2012 to 2018 was a period of continuous annual high annual growth and significant poverty reductions [Capuno 2022b].

reflected in the results, which could be driven by the majority of the sample or certain outliers. Thus, future studies should attempt to analyze household level data. While the current FIES module captures the amounts of transfers, the amounts are not apportioned according to source. The FIES income module could be revised to collect the amounts of 4Ps cash support received, if any, by the sample household.

Notwithstanding the loss in information for using aggregated data, our results are still credible given the 4Ps' expansive coverage within and across regions, and that the FIES samples are regionally representative. Extending the analysis to 2021 and 2024 rounds of the FIES could update our results, but must address the possible confounding effects of the prolonged lockdowns and other government assistance (*ayudas*) provided during the COVID-19 pandemic years.

All in all, our results provide some evidence that, while the 4Ps has yet to lift its beneficiaries out of poverty, it does pull them up from the depths of destitution. To make the program more effective, more cash transfers to the poor and less to the near poor could be provided, while making sure the added support does not disincentivize working and other income-earning activities.

Acknowledgments: This paper draws from a longer report [Capuno 2022a], which received a research grant support from the AC-UPSE Forum (through the UPecon Foundation), but also contains updated results and has benefitted from the excellent research assistance of Shey Cambel and Kath Gonzalvo.

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PRE The Philippine Review of Economics
62(1):127-160. DOI:10.37907/6ERP5202J

A macroeconomic perspective on economic resilience and inclusive growth in the Philippines

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There are at least two distinct but not equally important ways to understand what economic resilience means: one is focused on minimizing deviations of output about its trend and the quick return of output to trend following shocks, while another emphasizes the invariance of the underlying trend of output growth itself to shocks, including the ability to raise potential output despite shocks. The Philippine economy cannot be regarded as resilient using either definition.

Anemic growth and the lack of economic resilience in the Philippines are primarily due to the inability of the government to make sufficient and quality investments in critical public goods such as climate change adaptation, health, education, and IT connectivity. The main reason for the lack of public (as well as private) investment is the presence of weak institutions and poor governance, characterized by a political economy process which provides many opportunities for rent-seeking behavior that benefit a narrow set of interests, and where adherence and sensitivity to the rule of law is lacking.

Overcoming the problem of weak institutions and poor governance requires a change in the incentive structure faced by key institutions, with clear criteria and targets set and performance tied to tenure in office, so as to make government officials more accountable to the people. It requires a populace that demands accountability, transparency in motives and processes, and timely delivery of intended outcomes from the government, and an unwillingness to accept and trade off short-term token benefits for necessary investments to make growth robust, sustainable, and more inclusive. A well-informed and vigilant populace that demands adequate provision of quality public goods and services from the government is key.

JEL classification: O4, O5
Key words: economic resilience, inclusive growth, public goods, institutions, governance, rent-seeking

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1. Introduction

Economists clearly understand the concept of economic growth and have theories that explain how an economy's output can increase. Output grows when there is either an increase in the quantity of resources used to produce output, or improvements in technology that raise factor productivity and allow given resources to produce more output per unit than before, or both. If either or both of these occur, not only could an economy's actual output increase, but so would its so-called potential output.[1] Indeed, in a 2018 report entitled "Growth and productivity in the Philippines: winning the future", the World Bank states that "Sustaining high growth can only be achieved if the Philippines succeeds in sustaining high total factor productivity (TFP) growth while accelerating capital accumulation" [World Bank 2018:1].[2]

Inclusive growth is growth that aims to produce a more egalitarian society currently and across generations, and in which the creation of national wealth and the reduction of poverty are achieved by leveling the playing field without sacrificing economic freedoms [Agarwal 2024:8]. Inclusive growth is pro-poor growth. The focus is on both the process of growth, in which growth is more broad-based as more people are participants in the growth process, as well as on the outcomes of the growth process, in which the poor attain higher income levels and/or there is declining inequality in the income levels of the poor [Klasen 2010:1]. The inclusiveness of growth can also be assessed, for example, by measuring how many people move into formal employment from informal employment or unemployment, or are lifted out of poverty and live above a certain poverty threshold, or how the middle class, defined as those who reach a specific level of income, has grown. Good quality growth is expected to produce inclusive growth.

However, economists do not share a common understanding of economic resilience, as the concept encompasses a range of dimensions and interpretations.

Broadly, economic resilience refers to an economy's ability to withstand, recover quickly, and adapt to shocks while maintaining the economy's long-term growth potential. I propose at least two ways to understand what economic resilience means: one focused on stabilization of economic growth in the face of shocks, and another that emphasizes the invariance of the underlying trend of output growth itself to shocks, including the ability to raise potential output. I explain why the Philippine economy cannot be regarded as resilient using either definition. Furthermore, these distinct types of economic resilience are not equally important.

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[1] There is a difference between 'actual output' and 'potential output'. Potential output is what output would be if all available resources were employed. Actual output is simply what output is when available resources are used, noting that some of these could be unemployed.

[2] In economics, the term 'capital' refers to a produced good that is used as a factor of production to make other goods rather than being consumed immediately. As an example, if the grapes we have produced are not consumed today and are instead used as an input to make wine, grapes would be a capital good.

My thesis is that anemic economic growth and the lack of economic resilience in the Philippines are primarily due to the government's inability to make sufficient and quality investments in critical public goods such as climate change adaptation, health, education, and IT connectivity.

Moreover, there is a tendency to equate public investment in public goods solely or primarily with the building of physical infrastructure.

In his 2024 State of the Nation Address (SONA), for example, the President stated that:

> Aside from agriculture and disaster risk, our other vital sectors and pillars—such as education, health energy, low-cost housing, transport, information technology—they all stand to benefit from our aggressive infrastructure development, as befitting our upper middle-income economic target. With the results we have seen two years into this Administration, we can claim that despite challenges, we are progressing towards our targets in the medium-term. [Website of the President 2024]

Prioritizing the building of physical infrastructure appears to be the main understanding of what it means to invest in public goods. To improve health care access and delivery, especially for the poor, for example, the President highlighted building a UP PGH[3] Cancer Center and two specialty cancer hospitals, "Super Health Centers", a mobile clinic in every province, and first aid centers. Yet the main vehicle for making health care universal and affordable, and therefore accessible to the populace, especially the poor, PhilHealth,[4] seemed to be mentioned only in the context of expanding the list of generic medicines it would cover and raising the coverage caps for a few types of cancer treatment. This seems typical of an "ayuda" approach to health care access, rather than an investment-led one to address structural and institutional weaknesses in the health care delivery system. There was also no mention of the severe shortage of qualified health professionals in these hospitals and health facilities that are to be constructed. It is as if the supply of medical personnel will automatically increase if more hospitals are built.

As for meeting the challenges of natural and climate change-induced disasters, the President pointed to the need for the country to be prepared for these and then cited the almost one hundred evacuation centers built within the past two years. However, he made no similar reference to investments in technology for climate

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[3] The University of the Philippines Philippine General Hospital, or UP PGH, is a state-owned tertiary hospital designated as the National University Hospital and national government referral center. It is administered and operated by the University of the Philippines Manila.

[4] Philhealth, or the Philippine Health Insurance Corporation, created in 1995, is a tax-exempt government-owned and controlled corporation that administers the National Health Insurance Program (NHIP) in the Philippines. The NHIP aims to provide universal, accessible, affordable, and quality health care coverage to Filipinos and protect them from financial risks related to medical expenses. It is attached to the Department of Health. Source: Philippine Health Insurance Corporation website.

adaptation in areas such as agriculture, where the lives and livelihoods of farmers and fisherfolk are at risk due to changing weather patterns in the cultivation of rice and other crops, the acidification and warming of oceans, and the loss of biodiversity. Instead, he proudly announced the completion of more than 5,500 flood control projects and the ongoing building of more flood control projects in the entire country. This statement was widely applauded by the congressional audience he was addressing.

The main reason for this lack of public (as well as private) investment is the presence of weak institutions and poor governance, characterized by a political economy process loaded with opportunities for rent-seeking behavior that benefit a narrow set of people or interests, and where adherence to the rule of law is severely lacking. There is also a certain degree of path dependence due to missed opportunities in the past, keeping the economy in an unending catch-up mode.

The preference for building physical infrastructure appears to be directly linked to the opportunities for rent-seeking and corruption in it. The political cycle emphasizes rent-seeking while a politician is incumbent. This is myopic in that it fails to lay the groundwork for sustainable economic growth and resilience, even if it may occasionally offer a temporary respite from the effects of shocks. This is also why I regard the type of economic resilience that emphasizes laying the groundwork for long-term and sustainable economic growth over purely short-term stabilization considerations as being the more important one.

I provide a few examples of cases of underinvestment in some of these critical public goods in which poor outcomes are related to weak institutions and poor governance. While the lack of public investment in critical public goods, weak institutions, and poor governance are decades-long problems in the Philippines, I provide some evidence to show that the current administration under Ferdinand Marcos, Jr. has, thus far, a mixed record in addressing these challenges.

In terms of the government's record of public investments, the rate of year-on-year percentage change in capital expenditures by government as of September 2024 increased relative to those in the previous two years and is now at about the same rate it was in 2021, but this is still slightly lower than it was in 2016 [AMRO 2024:7]. While this is somewhat of an improvement, the administration's inability to improve governance and strengthen institutional capacity is the more serious challenge, and where little or no progress has been made. Some of this is evidenced by experience since the passage of the law creating the Maharlika Sovereign Investment Fund and in the process that attended the passage of the 2025 General Appropriations Act (GAA), expenditure priorities, and amounts allocated therein.

An early initiative from the Marcos Jr. administration was the Maharlika Sovereign Investment Fund, formerly the Maharlika Sovereign Wealth Fund. To this day, its *raison d'etre* remains unclear. With initial capitalization coming from two government financial institutions and the central bank, its ability to hasten the process of adding to the quantity of public investment remains largely untested, and its program of investments remains unknown beyond listing a menu of possible financial and real assets it can legally acquire. Thus far, the Maharlika Fund has not made any investment despite the Maharlika law having been passed in 2023. Hence, even the professed desire of the government to use Maharlika as the vehicle to speed up investment in critical infrastructure projects, by not being subject to the Government Procurement Act or being audited by the Commission on Audit for five years, for example, has not materialized.

Two years after the law's passage, Maharlika merely announced in January 2025 that it would acquire 20 percent of the 60 percent share of Filipino investors in the National Grid Corporation of the Philippines (NGCP).[5] This move, however, does not give the government control of the board of the NGCP. Hence, it is unclear how this move will allow the government to hasten or add to public investment in the energy sector and help reduce high electricity prices.

The process that attended the passage of the 2025 GAA, expenditure priorities, and the allocated amounts therein illustrate how rent-seeking has worsened under the present administration. The 2025 GAA is currently the subject of public commentary and disaffection, with several lawsuits filed before the Supreme Court questioning its constitutionality in not giving education the highest budgetary allocation and in expropriating a large amount of PhilHealth's funds to finance government budgetary requirements in areas other than health.

The bigger issue is the perception that Congress has not only inserted large amounts of pork into the national budget, especially that of the Department of Public Works and Highways, seen as the traditional source of corruption, but has done so by putting many priority programs, such as PhilHealth, the Basic Infrastructure Program, support to foreign-assisted projects, the Department of Agriculture's Rice Competitiveness Enhancement Fund, and others, under "Unprogrammed Appropriations," thereby effectively defunding them. "Unprogrammed Appropriations" itself is not a new concept. However, the humongous amounts ratified by Congress, ₱731.4 billion in 2024 and ₱531.665 billion in the 2025 national budget bills versus the Executive Department's limits of ₱281.9 billion and ₱158.7 billion in unprogrammed appropriations in its expenditure plans in 2024 and 2025, respectively, are. If anything, one is struck by the brazenness of Congress in shifting large chunks of the budget for many key

[5] In early February 2025, Maharlika announced the signing of a memorandum of understanding (MOU) with a Thai company, the CP Group, to put USD 100 million to establish a billion-dollar equity fund. The Maharlika President and CEO said that the proposed equity fund, "could be a potential source of future investments in the areas of agriculture, food production, digital innovation, and green energy. This fund will be a primary vehicle for deploying capital into these targeted sectors, driving growth and supporting innovative businesses that contribute to the Philippine economy" [Cigaral 2025]. Again, this underscores the fact that Maharlika is undercapitalized to undertake investments directly and has an unknown program of investments. Also, having only about a ten percent contribution to a billion-dollar equity fund means that Maharlika will not have control as to where the investments will be made. Importantly, only an MOU has been signed.

development projects of government to "Unprogrammed Appropriations" with seeming impunity, without seeing any need to explain or justify its actions.

The President sought to placate the public uproar by "studying" the proposed GAA for a week before signing the bill, eventually vetoing more than ₱195 billion in allocations, including ₱168 billion of unprogrammed appropriations, for a final amount of ₱363.665 billion in unprogrammed appropriations in the 2025 GAA [Bordey 2024]. Unfortunately, a presidential veto cannot restore funding to items that have not been given a budget allocation, such as PhilHealth, or defunded by Congress, such as climate adaptation projects of the Department of Environment and Natural Resources (DENR), and transport projects of the Department of Transportation (DOTr) such as the Metro Rail Transit and the subway system.

I conclude by highlighting the need to seriously address institutional weaknesses and poor governance to enable the government to invest in some particularly critical public goods. Overcoming the problem of weak institutions and poor governance requires a change in the incentive structure faced by key institutions, with clear criteria and targets set and performance tied to tenure in office, so as to make government officials more accountable to the people. It requires a populace that demands accountability, transparency in motives and processes, and timely delivery of intended outcomes from the government, and an unwillingness to accept and trade off short-term token benefits for necessary investments to make growth robust, sustainable, and more inclusive. A well-informed and vigilant populace that demands the adequate provision of quality public goods and services from the government is key.

The rest of the paper is as follows: Section 2 will discuss how the concept of economic resilience may be understood; Section 3 will discuss the possible constraints to producing sustainable and inclusive growth; Section 4 will cite some examples of institutional and governance weaknesses that give rise to the lack of government investment in health and climate change adaptation; and Section 5 will conclude.

2. Understanding economic resilience

Economic resilience refers to how an entity responds to a shock. There are many ways to describe what economic resilience means.[6] Here,

[6] See the various possible definitions and interpretations of "economic resilience." For instance, Rose [2007] discusses reducing losses from natural and man-made disasters in a static sense by using current resources more efficiently and in a dynamic sense by hastening recovery and rebuilding the capital stock. Martin and Sunley [2015] consider the spatial dimension—a regional level—of responses to and recovery from shocks. Briguglio et al. [2006] refer to the "nurtured" ability of an economy to withstand and recover from negative external shocks. The IMF [2021] similarly defines economic resilience as an economy's capacity to endure and recover from negative external shocks while quickly resuming normal operations, thereby minimizing the period of being unable to perform core functions. UNDP [2015] emphasizes the need for economies to withstand shocks like natural disasters through proactive risk assessment, addressing vulnerabilities, and building adaptive capacity. Caldera Sanchez et al. [2015] focus on preventing the build-

I present two ways to understand the concept of economic resilience drawn from a macroeconomic perspective.

One way is to imagine an economy using available resources and the current state of technology to produce output or GDP, smoothly moving along a particular GDP trend path over time. Of course, there are many reasons why an economy would not always be on its GDP trend path. Shocks could hit the economy and cause some resources to be temporarily unemployed (or overemployed) and output to fall below (or rise above) its trend path.

According to this definition, an economy is resilient if output remains relatively unaffected by any shocks that hit it by either staying on its trend or having only small output deviations from its trend and having output readily return to its trend.[7]

Another way to define economic resilience is when the underlying trend of output itself remains unaffected by economic shocks and/or when the output trend can increase endogenously through improved technology or a permanent rise in available resources. Suppose a substantial oil field is discovered, for example. Since oil is a resource used to produce output, the economy would have more resources available and could produce more. The so-called potential output would be higher than the original output trend indicated before the discovery of this resource.

Similarly, given a technological improvement or innovation that enables all existing laborers to produce more output, the trend path of output would be permanently higher relative to the original path.[8] It would be as if the economy were permanently endowed with more workers to produce more output in the original situation.

If the economy is resilient, the trend of output will be relatively unaffected by an adverse shock that hits the economy. But if the trend of output itself declines, or worse, experiences a structural break and is permanently shifted downward to a new lower trend path in response to an adverse shock, the economy would not be considered resilient by this definition.

In Figure 1, the dotted line shows the actual annual output level or GDP in the Philippines, measured in trillion pesos from 1981 to the third quarter of 2024.

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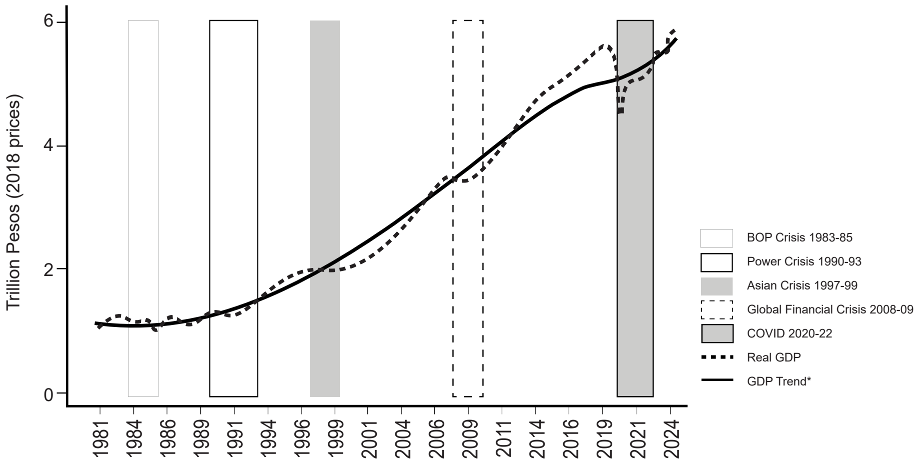
up of vulnerabilities, utilizing macro policies to mitigate the impact of shocks and accelerate recovery, and implementing structural policies that interact with macroeconomic policies to influence the speed of wage and price adjustments and the allocation of resources in response to shocks. De Bettencourt et al. [2013] advocate incorporating climate and disaster risk management into the development process, which contributes to the discussions on loss and damage under the UN Framework Convention on Climate Change.

7 This first definition proposed in this chapter is similar to the IMF definition of economic resilience.

8 New technology raises the amount of potential output. If it takes four laborers to make a cake per day without the use of an electric mixer, and I hire four laborers, using the current manual technology, one cake can be made in a day. However, if technology improves so that electric mixers are now available, and two laborers using one electric mixer can bake a cake in one day, then my original four laborers can potentially make two cakes using two electric mixers, or two cakes with one using two laborers and one electric mixer, even if the other two laborers were to make the cake manually, because of the improved technology available in both cases. 'Potential output' of four laborers—two cakes—is higher with better technology. It is as though we hired eight laborers in the situation with no electric mixers and using manual technology to bake cakes.

The solid line shows the underlying GDP trend. One can see that GDP or output falls whenever an adverse shock hits the economy, shown in the graph as bars, such as during the external debt crisis in 1983 to 1985, the power crisis in 1990 to 1993, the Asian Financial Crisis in 1997 to 1998, the Global Financial Crisis in 2008 to 2009, and the COVID-19 pandemic in 2020 to 2022. An output gap is created between the lines.

FIGURE 1. The Philippines' real GDP, Q1 of 1981 to Q3 of 2024



Source of data: Philippine Statistics Authority (PSA). Trend is calculated using the Hodrick-Prescott filter. GDP data are deseasonalized using the US Census Bureau's seasonal adjustment method (X13).

Figure 1 also indicates that the GDP level takes some time—approximately three years—to return to its pre-shock level following an adverse shock.

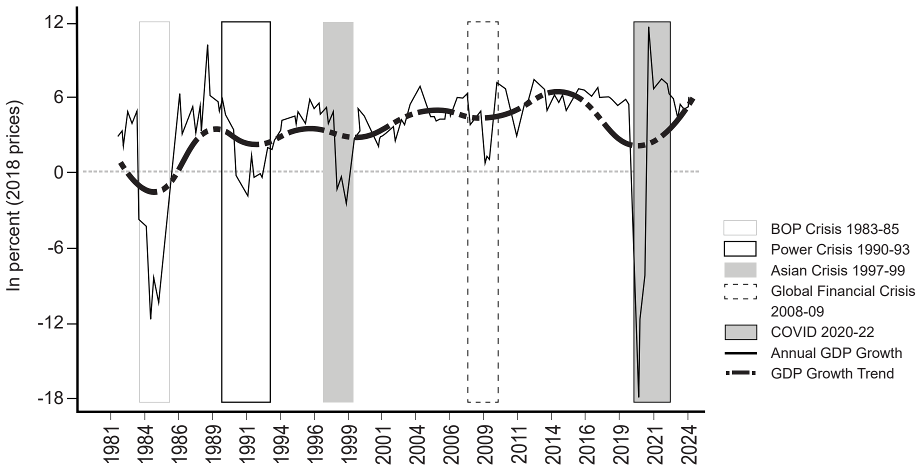
Thus, the economy cannot be regarded as resilient since adverse shocks lead to a fall in output and a deviation from trend, and it takes time to return to its trend.

When output deviates from its trend path, the government typically employs monetary and fiscal (government spending and tax) policies to bring the economy back to its trend path. The government responded to the COVID-19 pandemic shock by using expansionary fiscal and monetary policies. Net government spending and lending rose to 23.6 percent as a share of GDP in 2020 from 19.5 percent the year before. The government's debt-to-GDP ratio, which shows the amount of government borrowing to finance its expenditures relative to GDP, ballooned from 37 percent in 2019 to 51.9 percent in 2020. The monetary base grew by 5.1 percent in 2020 from a three percent contraction the year before [IMF 2021]. Despite these efforts, however, the economy's output registered a massive 9.6 percent contraction in 2020, the largest in the country's history.

Figure 1 shows that the trend in the level of GDP itself, the solid line, also exhibits a downward tilt beginning in 2020, with a flatter slope relative to its pre-pandemic slope.

Figure 2 shows the rate of GDP growth (in percent), or the rate at which the economy's level of output changes over time, shown as the solid line. As is evident, the GDP growth trend itself, shown as the broken line, fluctuates over time, with the bottom of large troughs during the BOP crisis in 1984 and the COVID pandemic crisis in 2020.

FIGURE 2. The Philippines' real GDP growth, Q1 of 1981 to Q3 of 2024



Note: Annual growth rates are calculated using quarterly data from Figure 1. See note in Figure 1.

Excluding the extreme 1984 to 1985 crisis years and the pandemic years of 2020 to 2022, one observes that the trend path of GDP growth is relatively flat, with an annual growth rate averaging around four to, at best, five percent, from the early 1990s up to the period right before the pandemic. Without these two extreme crises, this is the average GDP growth that had prevailed over the last three decades.

If these worst crisis periods are included, the annual average GDP growth rate would be much lower than four or five percent. The point is that over time, the economy has been unable to reach a high and rising growth trajectory nor sustain a high GDP growth rate.

Pre-pandemic, the World Bank estimated that the economy needed to grow at an annual average rate of 5.3 percent from 2000 onwards to triple its income over the next two decades and become a prosperous middle-class society free of poverty by 2040 [World Bank 2018:1].

Given COVID-19's hit on output growth, an even bigger catch-up is needed to make up lost ground. The possibility of a permanently lower GDP trend exists, either because of a decline in the slope of the original trend in GDP or because of a structural break in this trend that puts the economy on a permanently lower path.

Thus, it is evident that the Philippine economy is not truly resilient using either definition of economic resilience.

3. Possible constraints to producing sustainable and inclusive growth

The World Bank estimates that TFP needs to grow at an annual rate of 1.5 percent or higher until 2040 for growth to be sustainable and inclusive [World Bank 2018:8]. Similarly, to meet the capital accumulation requirement, a doubling of the growth rate in the physical investment-to-GDP ratio, through both private and public investment through to at least 2023 is needed and would require the implementation of important reforms [World Bank 2018:8].

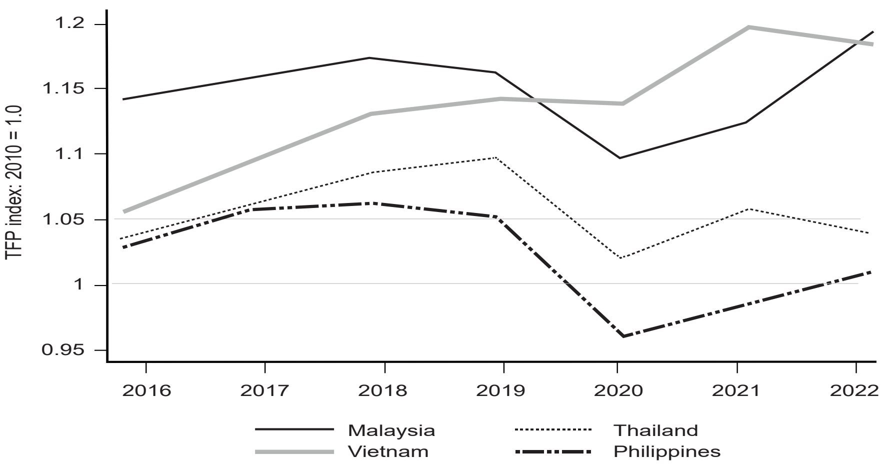
The same World Bank study [World Bank 2018:11] shows that TFP's contribution to growth has been variable since 2001, declining in 2006 to 2011 before rising in 2011-2016. TFP contributed about one-third of growth in the 2011 to 2016 period during the Aquino III administration as the economy registered robust growth.

However, the COVID-19 pandemic led to the largest decline in economic growth in the country's history of -9.6 percent in 2020. Factors of production became unemployed as output contracted. The unemployment rate doubled from 5.1 percent in 2019 to 10.4 percent in 2020.

The sharp decline in TFP during the COVID-19 years of 2020 and 2021 is illustrated in Figure 3, indicating that TFP in those years was lower compared to the base year of 2010. Although TFP recovered in 2022, it remains below pre-pandemic levels. The COVID-19 pandemic was not the sole reason for the low TFP; as displayed in Figure 3, since at least 2016, TFP in the Philippines has consistently been much lower than in Malaysia, Thailand, and Vietnam.

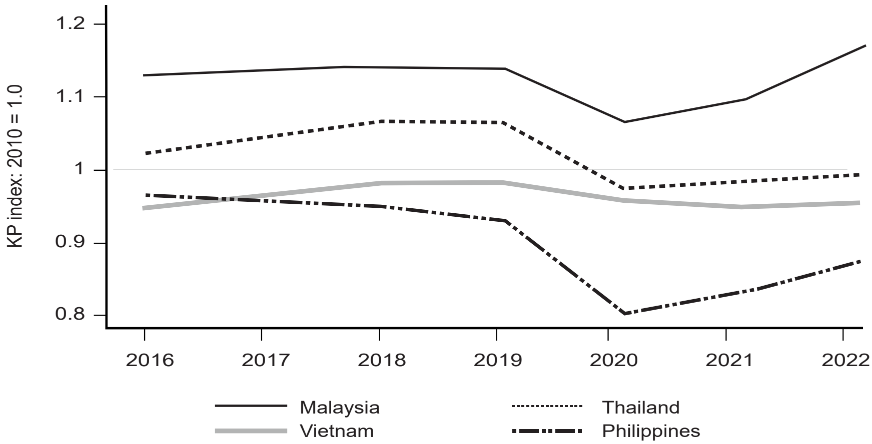
Capital productivity, shown in Figure 4, is extremely low and is the lowest compared with Malaysia, Thailand, and Vietnam. Again, this is not solely due to the pandemic, although the pandemic worsened capital productivity and brought it below the base year of 2010, recovering only to at least its 2010 level by 2022, but still at below pre-pandemic levels.

FIGURE 3. Total Factor Productivity, 2016 to 2022



Source of basic data: APO productivity database.

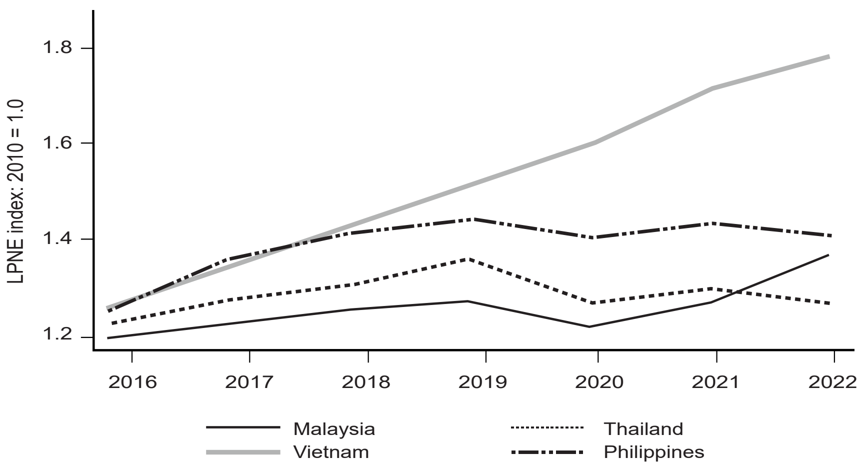
FIGURE 4. Capital productivity from 2016 to 2022



Source of basic data: APO productivity database.

Labor productivity since 2010, shown in Figure 5, was rising until the pandemic struck. The data show that labor productivity has remained fairly flat since 2020, unlike the rising trend displayed by Malaysia and the spectacular one by Vietnam. An article on labor productivity based on World Bank data in 2023 [Businessworld 2024], measured as GDP or output per person employed, in 2021 US dollars, shows that the Philippines has the fifth lowest level of labor productivity in the region at USD 23,519 in 2023 even though labor productivity grew by two percent year-on-year in 2023. This level of labor productivity is more than two times lower than the East Asia and Pacific regional average of USD 43,715 and the world average of USD 47,919 in 2023.

FIGURE 5. Labor productivity (based on number of employment) from 2016 to 2022



Source of basic data: APO productivity database.

Why is labor productivity in the Philippines so low? The World Bank [2018:11] states that "Low labor productivity is caused in part by *historic* (emphasis, mine) low levels of capital accumulation, resulting in low capital per worker, which limits labor productivity growth despite higher TFP growth." In other words, the Philippines has failed to invest sufficiently in the past so that it does not have a large capital stock. This problem did not arise only because of or during the COVID-19 pandemic, although gross fixed capital formation did collapse by 27.5 percent year-on-year in 2020 relative to what it was in the previous year [IMF 2021].

This low stock of capital, given historically low levels of capital accumulation or investment, adversely affects labor productivity. Consider this simple example. A sewing machine is a capital good, and if every worker were equipped with a sewing machine, more dresses could be made in a day compared with the case where workers make dresses using hand stitching alone. Capital per worker in the Philippines is less than half of what it is in Indonesia and Malaysia [World Bank 2018:10].

According to the World Bank study [2018:11], Indonesia and Malaysia display a greater contribution to output growth due to capital than the Philippines does. In Vietnam, which receives a large share of foreign direct investment (FDI), capital is the main contributor to output growth. Not surprisingly, Vietnam has very high labor productivity.

The World Bank advocates (i) the improvement of market competition through regulatory reforms to reduce the costs of doing business and discourage inefficient firms and (ii) improving trade and investment climate policies and regulations by liberalizing foreign equity restrictions and removing barriers to entry, to raise TFP and increase capital accumulation [World Bank 2018:8-9].

While not denying the importance of these, the World Bank policy reform agenda puts much of the onus on the market system and the private sector. The government is primarily regarded as taking on a more laissez-faire, hands-off role to ensure that the private market system works better and as it is supposed to. And we have made great strides over the years in enhancing competition in the economy by dismantling monopolies, decontrolling interest rates, enhancing bank competition by opening the banking sector to foreign bank entry, liberalizing trade, redefining the scope of public services to allow foreign entry, all of which have contributed to greater efficiency in the economy.

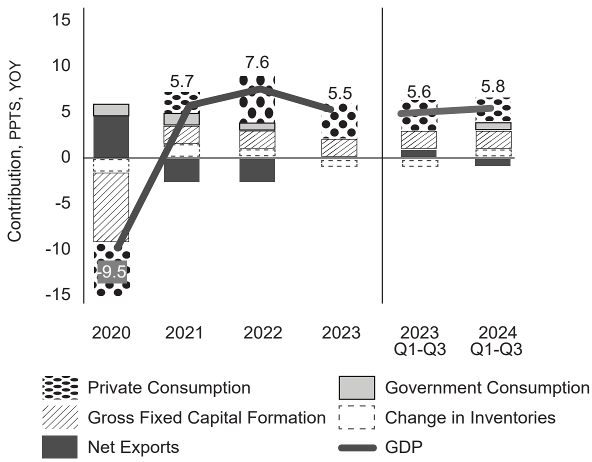
The fact is, however, that not all goods can be produced efficiently or in sufficient quantity by the private market. Market failures do exist.

In my view, the failure of government to provide sufficient amounts and quality of certain critical public goods is a more important binding constraint to sustainable and inclusive growth, rather than the failure of the government to enhance market competition and efficiency. This failure limits or hurts TFP growth and capital accumulation. These critical public goods are in the areas of climate change adaptation, health, education, and IT connectivity.

The Philippines has historically had a very low level of public investment average of 2.5 percent of GDP per year, versus 3.8 percent of GDP in the region, over the period 1998 to 2015 [World Bank 2018:36]. This low level of public investment has been a feature of the Philippine economy for at least 17 years.

Figure 6 shows that real GDP growth in the Philippines is driven primarily by private consumption, shown by the spotted bars. When private consumption contracts, as it did in 2020, GDP growth also declines significantly; conversely, when consumption rises—as in 2022—GDP growth increases accordingly. It is followed by government spending, shown by the light gray bars, and then to a smaller extent by gross fixed capital formation or investment (both public and private), shown by the diagonal line bars, and finally by net exports and changes in inventories, shown by the dark gray bars as in 2022.

FIGURE 6. Real GDP growth by expenditure from 2020-Q1 2024

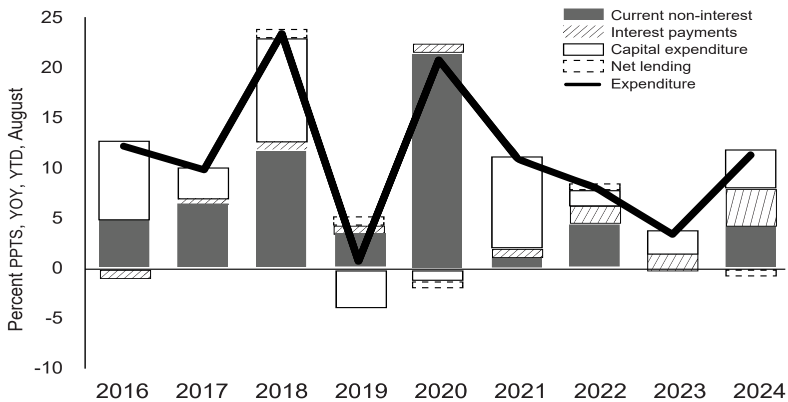


Source: PSA and AMRO Staff calculations in AMRO [2024:5]

Figure 7 shows the changes in types of government spending since 2016. Of particular interest are the capital expenditures of the government, shown by the light gray bars. Relative to 2021, capital expenditures of the government fell in 2022 and 2023, the first two years of the Marcos Jr. administration, before increasing in August 2024. However, even this growth in public expenditure on capital in August 2024 is lower than those in the pre-pandemic years of 2016, the end of the Aquino administration, and 2018, during the Duterte administration. Relative to the past two administrations, therefore, the present administration, thus far, has an inferior record in increasing public investments, only approximating the Duterte administration's record in 2021 post-pandemic.

The main reason the government has been unable to invest in certain critical public goods is due to weak institutions and poor governance. In large part, the political economy process involved in crafting laws and formulating and implementing policies provides enormous opportunities for rent-seeking behavior to benefit favored individuals or groups. This is neither a new insight nor phenomenon but appears to have become more evidently acute today.

FIGURE 7. Changes in government expenditure from 2016 to August 2024



Source: DBM and AMRO Staff calculations AMRO [2024:7]

Infrastructure projects are a traditional source of budgetary allocation and corruption, with many such projects awarded to “spurious contractors often owned by the very politicians who allocate the funds for them” [Habito 2024]. There appears to be more than a whiff of potential conflicts of interest and disregard for the rule of law. For instance, many in Congress, including both the Speaker of the House and the former Chair of the House Appropriations Committee, are or were among the largest contractors in the country.[9]

[9] Martin Romualdez was first elected Speaker of the House of Representatives in 2022 and currently still serves in this capacity [Source: Wikipedia]. In 2023, and hence, already during his incumbency as Speaker, he bought a 20 percent stake in EEI, one of the largest construction firms in the country, for ₱1.25 billion through his RYM Business Management Corporation [Camus 2023]. In March 2025, it was reported that Romualdez had divested from EEI and that the President and CEO of EEI himself bought Romualdez’ RYM Business Management Corporation’s entire stake. Curiously, not only did this happen shortly after the controversy surrounding the 2025 national budget that Congress had passed had erupted, but also, it appears that the Speaker sold his shares at a loss since the acquisition price of RYM’s 207.26 million EEI shares had a market value of only about ₱ 829 million, much lower than the ₱ 1.25 billion Romualdez had paid to acquire these shares in 2023 [Loyola 2025].

The Chair of the powerful House Appropriations Committee in the same 19th Congress and a very close ally of Speaker Romualdez, Elizaldy or Zaldy Co of the Ako Bicol Party List group, owns or owned Sunwest Construction and Development Corporation (SCDC), founded in 1997 and one of the biggest government contractors in the country. SCDC has undertaken many government infrastructure projects throughout the years, including building the Bicol International Airport. SCDC eventually became more diversified, with many affiliate companies and subsidiaries under the holding company, Sunwest Group Holdings Incorporated.

By 2009, before Zaldy Co himself became a member of Congress. SCDC was the DPWH’s fifth largest contractor. In 2024, DPWH contracts in the Bicol region secured by SCDC amounted to more than

Congress has been able to carve out large chunks from the General Appropriations Act (GAA) for their pork barrel projects by pre-identifying and inserting these into departmental or line agency budgets.

Data show that of the infrastructure projects of the Department of Public Works and Highways (DPWH) in the past three budgets, 44 percent have been for "roads, bridges, and multi-purpose halls", and about 20 percent has gone to flood control projects [Punongbayan 2024;2022]. Of the ₱1.5 trillion of the DPWH in 2024, for example, more than half are taken up by only two infrastructure projects: ₱521.3 billion is for the road network while ₱352.8 billion is for flood control projects [DBM 2024].

Given these disproportionate allocations for infrastructure, and the potential conflicts of interest arising from some members of Congress who allocate funds for these having ties to or being government contractors themselves, the opportunities for rent seeking appear unconstrained and unbounded.

₱5.7 billion, behind only two other firms. Between 2016 and 2024, it is estimated that SCDC won government projects worth at least ₱38 billion, based on data available on the DPWH website. In 2019, for example, SCDC bagged 12.16 percent worth ₱3.792 billion of the total value of contracts in Bicol of ₱31.126 billion and by 2022, but this already large amount rose to ₱10.465 billion or 15.13 percent of the total value of contracts in Bicol of ₱69.152 billion [de Leon and Valmonte 2025].

Co was first elected to Congress in 2019, the same year he supposedly divested from SCDC, apparently to be compliant with the avoidance of conflict of interest prescribed in the Code of Conduct and Ethical standards for Public Officials and Employees. At least on paper, therefore, there was a period in the recent past when Co was already in Congress and SCDC was a large government contractor before he divested from SCDC. However, Co is allegedly still the "beneficial owner" of SCDC as he remains a shareholder in several Sunwest-linked firms doing business with SCDC [de Leon and Valmonte 2025]. Following the brouhaha over the 2025 national budget which he was instrumental in crafting, in January 2025, Co lost his post as chair of the powerful House Appropriations Committee, a position which essentially bestows on the holder power over the public purse, after the President's Congressman son made a motion in the House declaring the chairmanship of the Committee vacant which was approved. Co appears to have been the fall guy from the fallout in the aftermath of the controversial 2025 national budget, likely to protect higher ups [de Leon 2025].

SCDC is a scandal-plagued corporation, also allegedly involved in the Pharmally scandal--a small company called Pharmally, with a capitalization of less than ₱1 million, was able to secure billion-peso government contracts for the procurement of masks and other personal protective equipment during the COVID pandemic, and which equipment also turned out to be of poor quality; in 2023, SCDC's audited financial statement showed that its revenues from the sale of personal protective equipment had revenues of ₱11.694 billion in 2022, equivalent to almost 18 percent of its total revenues [de Leon and Valmonte 2025], and the DepEd laptop scandal, pertaining to the delivery of overpriced and outdated and therefore unusable laptops procured by the DepEd [de Leon and Valmonte 2025]. The alleged involvement of Co and Sunwest in these scandals came to light in a privilege speech delivered by then Senate Majority Leader Joel Villanueva [Bordey 2024].

It should also be noted that the Chair of the House Committee on Accounts in the 19th Congress, Yedda Romualdez of the Tingong Party List group, is the wife of Speaker Romualdez. The Committee on Accounts has jurisdiction over the internal budget of the House, including accounting, budget preparation, disbursements, financial operations, and submission and approval.

This triumvirate of the Speaker, the Chair of the House Appropriations Committee, and the Chair of the House Committee on Accounts wields almost absolute power over the disbursement and allocation of public funds, including congressional pork barrel projects.

Legislators also dole out financial and medical assistance for their projects through pork inserted into the DSWD's and DOH's budgets as people would need to approach them and get them to issue guarantee letters (GLs) to cover medical bills, for example. While giving PhilHealth a zero subsidy in the 2025 budget, cutting billions from the Department of Education's budget and not allotting the biggest share of the budget to education, as constitutionally mandated, Congress has instead allotted ₱26 billion to a cash assistance program for minimum wage earners and the near poor called *Ayuda sa Kapos ang Kita Program* (AKAP). Given the uproar that attended this allocation to AKAP, which many view as a means for politicians to bribe voters for the May 2025 mid-term election, the President placed AKAP under conditional implementation. The Budget Secretary stated that the AKAP budget will be released only once guidelines are in place and are met by the agencies—the Departments of Social Welfare and Development, Labor, and the NEDA [Esguerra 2024].

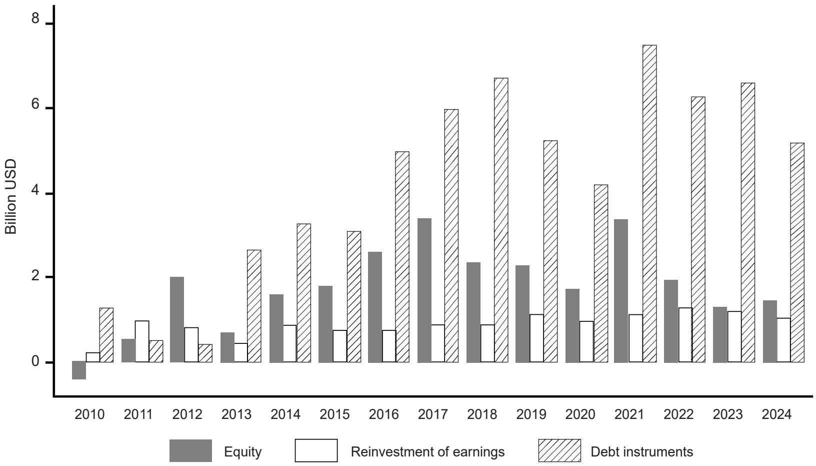
Congress can protect the budget for its pork barrel projects without increasing the approved budget in the GAA by simply designating large chunks of a department's budget as "unprogrammed appropriations." The latter means that departments cannot spend this portion of their allotted budgets unless the government has excess funds to fund them. In the face of a declared policy of "no new taxes," and the need to cover "unprogrammed appropriations," the need to find excess funds elsewhere in the government, including government-owned and controlled corporations (GOCCs), explains why the DOF took and continues to attempt to take back all ₱89.9 billion from PhilHealth to fund government spending in areas other than health.

Adherence to the rule of law is weak and the judiciary, probably the most critical institution for a well-functioning democracy and economy, is also not regarded as fair nor free of corruption. This is especially damaging to the ability of the country to attract foreign investors, especially foreign equity investors.

When investor rights are not secure and the risk of expropriation is high, investors will be wary of investing here. A study by Ma and Wei [2020], for example, shows that the composition of foreign capital inflows is adversely affected by poor institutional quality, proxied by a high risk of expropriation. This is because the informational requirements in equity investment are far greater than those in debt-financed investment. A debt instrument requires less information since the interest rate, maturity period, face value, and rate of return are already known when an investor buys debt paper and holds the security to maturity. In contrast, the rate of return on an equity investment is unknown *a priori.*

Ma and Wei [2020] show that when institutional quality is poor, equity investment will be inefficiently low—because equity financing is more vulnerable to expropriation risk than is debt investment—and total capital inflows will consist of a high share of debt. Perhaps this poor quality of institutions is the reason, as Figure 8 shows, that the composition of foreign capital flows to the Philippines consists mostly of debt, rather than equity flows.[10]

FIGURE 8. Composition of foreign capital flows to the Philippines from 2010 to October 2024



Source of basic data: Bangko Sentral ng Pilipinas (BSP).

One other thing that needs to be noted is the fact that many government agencies and departments lack the technical capacity to formulate and implement programs and projects to spend their budgetary appropriations properly. For years, there has been underspending by government agencies and departments. This has been and is also still being used to justify taking 'surplus' funds from these agencies and departments and reverting these to the National Government.

Another factor that contributes to institutional weakness and poor governance is the seeming inability of supposedly technically competent government officials to influence policymaking sufficiently or significantly, and/or devise ways to reduce or disincentivize rent-seeking behavior. Some are induced to remain quiet to be able to obtain or remain in what are oftentimes sinecure positions. The idea for the Maharlika Fund, for example, was apparently initially floated by a top government economic manager, and the bill to create Maharlika was subsequently sponsored by some of those who regard themselves as being the economists in Congress.

Being a deficit country means the country does not have surplus funds to set up a sovereign wealth fund or sovereign investment fund. The Congressional sponsors of the bill initially attempted to secure Maharlika's capital from the government's pension systems, GSIS and SSS. Due to the public backlash, this proposed action was not pursued. Government financial institutions (GFIs), the Development Bank of the Philippines (DBP) and Land Bank of the Philippines (LBP), were targeted next and were each required to cough up ₱50B and ₱75 billion,

[10] This hypothesis can be empirically tested.

respectively, while the central bank, the Bangko Sentral ng Pilipinas, or BSP, was to initially contribute ₱50 billion from its earnings. This demonstrates weak adherence to the rule of law—Congress can just pass laws to justify, *ex-post*, the confiscation of part of the capitalization of government financial institutions and the BSP, contravening the law that created an independent BSP and the charters of both DBP and LBP.

The decapitalization of DBP and LBP led these GFIs to request regulatory forbearance from the BSP to meet capital adequacy requirements. The independence of the BSP took a hit, and its operational independence could also be seen as being compromised by the requirement to generate profits to fund Maharlika, where its primary mandate is the control of inflation. As the regulator of banks, the BSP could not say or do anything to prevent Congress from requiring government financial institutions like LBP and DBP from being depleted of their capital, contrary to what a bank regulator would have any banking institution it supervises and regulates do.

4. Some examples of institutional and governance weaknesses associated with poor outcomes

Example no. 1: The country's experience during the COVID-19 pandemic

The Philippines was not expected to be the worst-performing country in the ASEAN +3 region post-pandemic.

This is because the Philippines had 'strong macroeconomic fundamentals' pre-pandemic. It enjoyed a decade of high growth, including a 6.7 percent growth rate of output in the fourth quarter of 2019. Inflation was low and stable at an average of 2.4 percent year-on-year in 2019. Its tax revenue-to-GDP of 16.1 percent pre-pandemic was the highest it had been since 1997. Its debt-to-GDP ratio of 39.6 percent was the lowest recorded since 1986, and it was enjoying its highest-ever sovereign credit rating of between BBB+ and A-.

In short, all the usual macroeconomic metrics pointed to a healthy and robust economy. Yet, as shown in Table 1, the IMF projected that the Philippines would have the largest reversal in GDP growth from 2019 to 2020 and the largest contraction in output growth in 2020 among countries in ASEAN +3.

This is puzzling since Table 1 also shows that, apart from the CMLV countries,[11] in 2019, the Philippines had the second highest annual GDP growth rate of six percent, second only to China's 6.1 percent.

[11] Cambodia, Myanmar, Laos, and Vietnam. These countries started out as being the less developed countries in ASEAN, especially compared to the original ASEAN 5 countries. They are starting from a lower base and therefore tend to have higher rates of growth as they transition to more market-based economies and become more developed. Of course, Vietnam has become a star performer in the region following its earlier Doi Moi economic reform program.

TABLE 1. 2020 GDP Growth Forecast, ASEAN +3

	Annual percent change in real GDP		
Country	**2019**	**2020 forecast**	**Drop**
Brunei	3.9	0.1	3.8
Cambodia	7.1	-2.8	9.9
China	6.1	1.9	4.2
Indonesia	5.0	-1.5	6.5
Japan	0.7	-5.3	6.0
Lao PDR	5.0	0.2	4.8
Malaysia	4.3	-6.0	10.3
Myanmar	6.8	2.0	4.8
Philippines	6.0	-8.3	14.3
Singapore	0.7	-6.0	6.7
South Korea	2.0	-1.9	3.9
Thailand	2.4	-7.1	9.5
Vietnam	7.0	1.6	5.4

Source: Tables A3 and A4 and IMF [2020] from Monsod and Gochoco-Bautista [2021].

Monsod and Gochoco-Bautista (MGB) [2021], hypothesized that the severe and long lockdown resorted to was due to its being regarded as the only instrument available to prevent the transmission of COVID-19. The reason behind the almost exclusive reliance on such a containment measure may have been the lack of health system capacity and preparedness to manage pandemics, rather than the lack of fiscal resources to deal with the pandemic's effects *per se*. This hypothesis is tested in this paper.

The World Health Organization's (WHO) International Health Indicators (IHR) "require states to maintain capacities to detect, assess, and respond to events that may constitute a public health emergency of international concern" [MGB 2021]. IHRs in 2019 for some countries in the region were compared to see the preparedness of a country's health institutions across different types of health capacities.

The 2019 score per capacity for six of 13 indicators associated with detection and response capacities in the Philippines and Vietnam, for example, relative to the global average and the WHO regional average, shows that the Philippines is further away from global and regional averages while Vietnam is much closer to them.

On one indicator in particular, laboratory, the Philippines significantly lags Vietnam. During a pandemic, the ability to detect COVID-19 cases and isolate and treat such cases relies on being able to test for it by having a laboratory capacity that can handle many cases at once, and obtaining lab results quickly.

Vietnam's demonstrated daily capacity at the end of April 2020, was 0.27 per 1,000 people, which was almost seven times greater than that of the Philippines of 0.04. The Philippines had only one lab capable of doing RT-PCR testing at the start of the pandemic and only reached Vietnam's testing capacity in July 2020 [MGB 2021]. Not surprisingly, the daily new confirmed COVID-19 cases per million people in the Philippines was much higher than Vietnam's. COVID-19 transmission in the Philippines continued to be classified by the WHO as "community transmission" as of October 2020, whereas Vietnam's was described as "clusters of cases" [MGB 2021]. COVID-19 outcomes were dismal as well. The Philippines had the highest number of total confirmed COVID-19 cases in ASEAN +3 and by October 2020, the Philippines' death rate from COVID-19 per 1 million population was the highest in ASEAN +3. Thus, on both the economy and COVID-19 outcomes, the Philippines was the bottom dweller in ASEAN +3.

The government used expansionary policies, particularly fiscal policy, to support the economy. What explains the bleak outcomes in output growth from the pandemic response?

MGB [2021] formally test the factors that correlate with the projected decline in GDP growth in 2020 from 2019 in ASEAN +3 countries, developing East Asia, South Asia, Australia, and New Zealand. Such factors include a measure of a country's health capacity, a country's fiscal position, the susceptibility of a country to the disease, and a measure of the vulnerability of a country to external shocks such as COVID-19, using pre-COVID data.

They find that *ceteris paribus*, stronger national health capacities to detect and respond to disease outbreaks are associated with better economic outcomes in 2020. Specifically, improvements in certain institutional health capacities, such as laboratory capacity, may matter more than other correlates, including the amount of fiscal spending to respond to COVID-19.

In fact, they find that a strong fiscal position prior to 2020 is either not statistically significant in explaining the drop in GDP from 2019 to 2020 or is statistically significant in the wrong direction. This suggests that is not the amount of government spending that may matter for good COVID-19 health outcomes *per se*, but whether such spending is leveraged optimally. While necessary during the pandemic, income support, for example, did not help resolve long-standing institutional issues in the health preparedness and response system and thus, did not prevent the almost exclusive reliance on long and severe lockdowns to contain the pandemic and the subsequent large drop in GDP growth in 2020 as well as the poor COVID-19 outcomes.

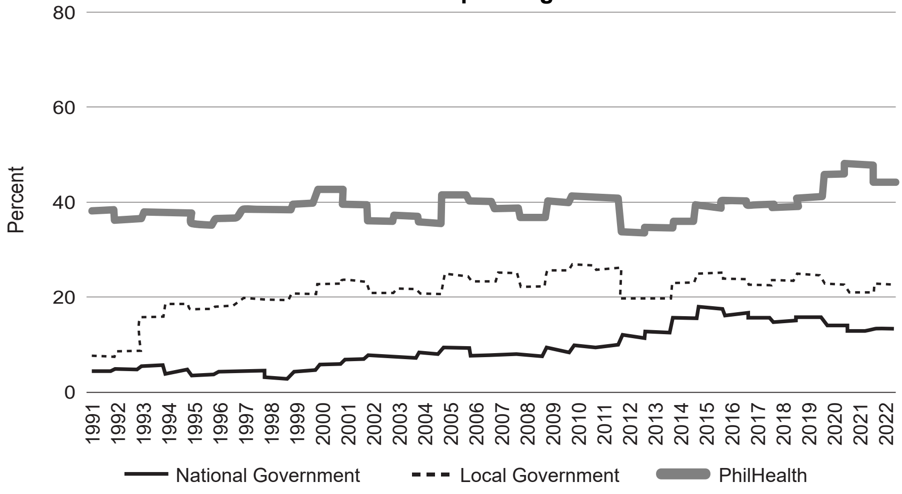
Example no. 2 The country's health system

In a review of the Philippine healthcare system, Panelo et al. [2017:3] assess the long-term impact of healthcare reforms on health outcomes over the past 25 years. They cite persistent fundamental structural weaknesses that have prevented these reforms from having the intended beneficial health outcomes. They also note that progress in health outcomes, relative to neighbors in the region and the attainment of Millennium Development Goals (MDGs), has been slow in the Philippines.

The health system has suffered and continues to suffer from a lack of public investment and expenditure on health.

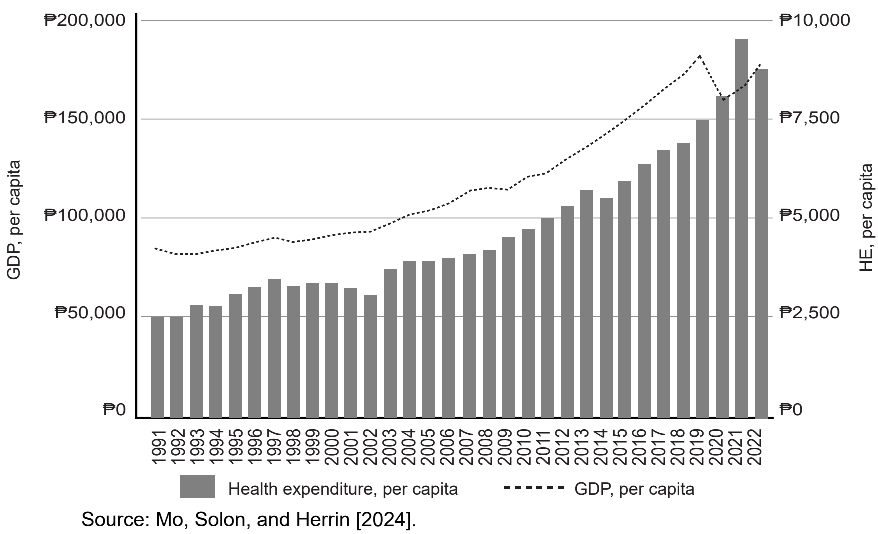
Figure 9 shows that total public spending on health, composed of the shares of the National Government, local governments, and Philhealth, the social insurance scheme, has remained the same at roughly 40 percent of total health expenditure since 1991, or for about three and a half decades. What is noteworthy about this is the fact that the 40 percent share of aggregate public spending in total health expenditures is still way below the 70 percent set in the DOH's Health Sector Reform Agenda (HSRA) target in 1999, or over twenty years ago.

FIGURE 9. Public spending on health



Source: Mo, Solon, and Herrin [2024].

FIGURE 10. Total health expenditure in real per capita terms



Source: Mo, Solon, and Herrin [2024].

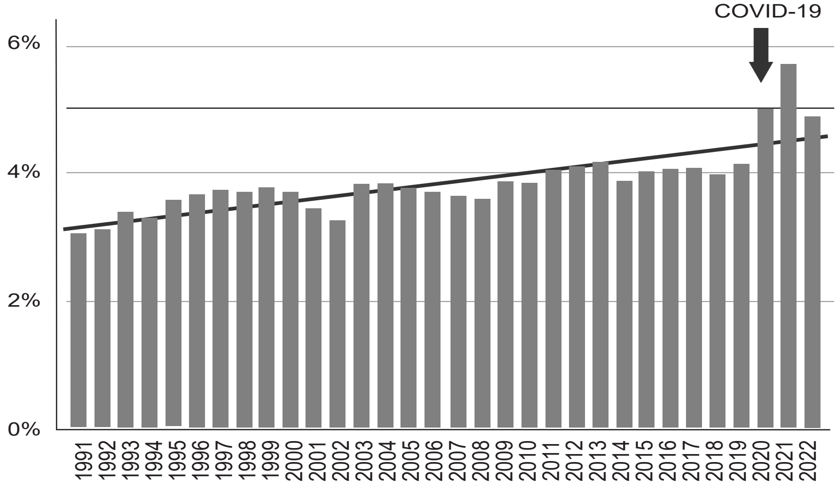
While the share of public spending in total health expenditures has remained relatively unchanged, the composition has changed, with Philhealth's share growing while the local governments' share declining.

Total spending (public and private) on healthcare has grown over a 30-year period by a factor of 30, from ₱40.3 billion in 1991 to ₱1.1 trillion in 2022, averaging 5.84 percent per annum.

However, real per capita health spending, shown in Figure 10, has only grown by a factor of 3.4 over the last 30 years, from ₱2,542 in 1991 to ₱8,658 in 2022, clearly very much less than growth in total nominal health expenditures, due to both about a doubling of the population between 1991 and 2022, and to inflation [Ma, Solon, and Herrin 2024].

Figure 11 shows that for three decades, since at least 1991, the WHO target of five percent of total health expenditures of GDP has been missed. Only in 2021, at the height of the pandemic, did this ratio exceed five percent.

FIGURE 11. Health expenditure, share of GDP

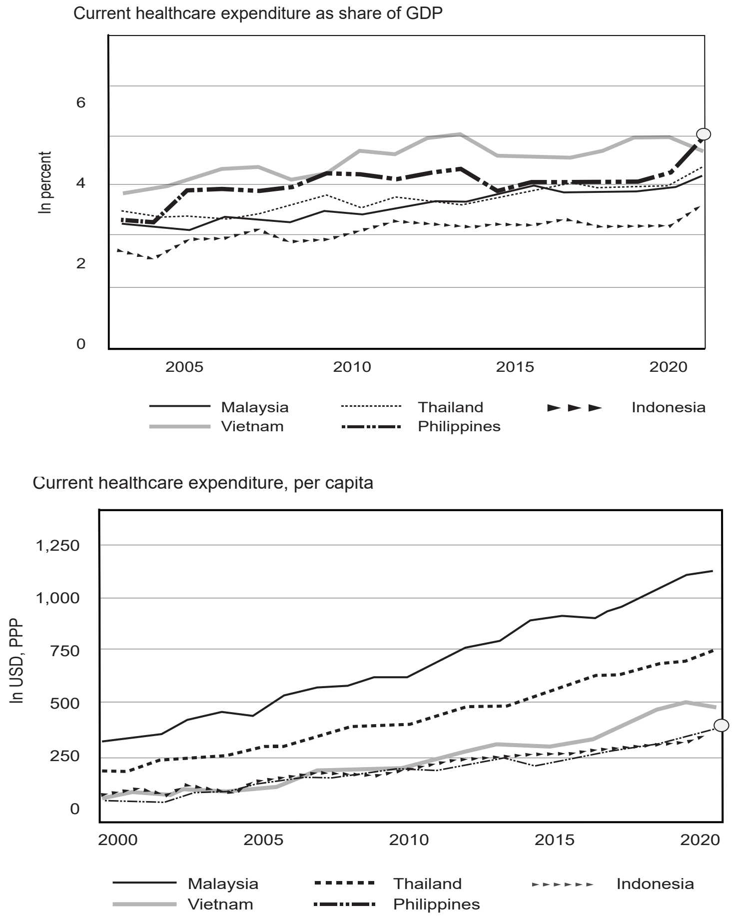


Source: Mo, Solon, and Herrin [2024].

Relative to regional peers, the upper graph in Figure 12 shows the while the Philippines compares favorably in terms of health expenditures as a share of GDP, because of anemic GDP growth over the last three decades, the Philippines lags behind its regional peers in current per capita healthcare spending in absolute terms, as shown in the lower graph.

The counterpart of the lack of government investment in the health system and in paying for health expenses is the large share of out-of-pocket (OOP) payments, amounting to 45 percent of total healthcare expenditure payments in 2022. Meanwhile, the National Government accounts for 21 percent, Social Health Insurance for 14 percent, and Local Government for ten percent of total healthcare expenditure payments [Ma, Solon, and Herrin 2024].

FIGURE 12. Healthcare expenditures as a share of GDP and current, per capita in comparison with regional peers



Source: Mo, Solon, and Herrin [2024].

If people pay for almost half of total health expenditures out of their own pockets, this is a barrier that tends to exclude people, especially the poor, from accessing medical care.

Large OOP costs and the unaffordability of better-quality healthcare by the poor can also be inferred from the utilization of different types of health facilities by wealth profile.

Data from 2013 in Table 2 show that the poor primarily use public health facilities. Nine out of ten (91.4 percent) of the poorest use public health facilities. More than half of the poorest, 55 percent, go to the barangay health services (BHS), which provide only very basic health services. Only 8.6 percent of the poorest people go to a private health facility. In contrast, 73.6 percent of the wealthiest people go to private health facilities while only 8.6 percent of the poorest people do so.

Except for public tertiary hospitals. primarily UP PGH and a few other large ones such as East Avenue Medical Center, National Kidney and Transplant Institute, private hospitals are generally regarded as being able to provide better quality health care.

TABLE 2. Utilization of health facilities by wealth quintile

	Public	DOH hospital	LGU hospital	RHU	BHS	Private	Private hospital	Private clinic
All	67.1	5.1	11.1	18.7	32.2	32.9	20.3	12.7
Poorest	91.4	3.8	9.3	23.3	55.0	8.6	4.6	4.0
Poor	84.2	4.1	13.0	25.2	41.9	15.8	9.0	6.8
Middle	71.7	6.1	12.7	22.3	30.4	28.3	15.8	12.5
Rich	50.5	6.5	12.0	13.4	18.6	49.5	31.6	17.9
Richest	26.4	5.2	8.0	6.0	7.3	73.6	47.6	25.9

Source: Panelo, Solon, Ramos, and Herrin [2017:20] based on data from UPecon-HPDP calculations and NDHS 2013.

Health outcomes are poor, as key metrics indicate. The maternal mortality ratio per one hundred thousand births has barely changed over 25 years, decreasing from 209 in 1990 to 204 in 2015, despite the target being set at 52 by 2015. Similarly, the prevalence of underweight children under five years old has also shown little change during this time, declining from 26.5 in 1992 to 21.5 in 2015, while the target was set at 13.1 by 2015 [Panelo et al., 2017:5].

According to the SDG Indicators of the Philippine Statistics Authority (PSA), only 56.9 percent of currently married women of reproductive age (15-29 years of age) have their need for family planning satisfied (provided) with modern methods, while the target is for 100 percent coverage by 2030 [PSA 2022]. The PSA SDG also shows that the percentage of public health facilities properly stocked with selected essential medicines is only 56 percent in 2020, a decline from 65.4 percent in 2016.

In rural areas, where the majority of the poor live, few doctors have undergone advanced training. Data for 2016, for example, show that an overwhelming majority of the surgeons who have completed fellowships mainly practice in large urban centers: 1,295, practice in the National Capital Region (NCR), followed by CALABARZON[12] with 193, and Central Luzon with 192. Only 17 practice in MIMAROPA,[13] 22 in Caraga, and one in the Autonomous Region of Muslim Mindanao (ARMM) [Panelo et al., 2017:24].

In short, key health outcomes are dismal and have not changed much in three decades. Targets set in terms of the share of public spending of total health expenditures have been missed over many decades. The lack of public spending on health goods and services and financing is reflected in very high OOP expenses,

[12] This is the region that comprises the provinces of Cavite, Laguna, Batangas, Rizal, and Quezon.

[13] This region includes the provinces of Mindoro, Marinduque, Romblon, and Palawan.

averaging 45 percent of total health expenditures, which prevents the poor from being able to access quality healthcare. The only memorable pronouncement made by the President during his latest SONA is the plan to have more specialty hospitals established in areas outside the National Capital Region to try and make quality healthcare accessible to far-flung areas.[14]

Despite all these, Congress has chosen to give a zero subsidy to PhilHealth in the 2025 budget and expropriated ₱60 billion of a planned ₱79.9 billion from PhilHealth's reserve fund to spend on other programs and projects of government that have been relegated to "Unappropriated Expenditures" of the GAA. The Solicitor General of the Philippines and Office of the Government Corporate Counsel (OGCC), representing the government, argued before the Supreme Court that the money taken from PhilHealth is not part of PhilHealth's reserve fund but is instead the excess of PhilHealth expenditures on indirect beneficiaries, such as senior citizens and persons with disabilities, relative to the government's PhilHealth subsidy for these.[15]

The government has chosen to justify the legal basis of its actions in expropriating PhilHealth's funds, but its argument misses the point: It is not the origin of the funds from PhilHealth that matters, but the fact that there are unused funds at PhilHealth. These unused funds represent an opportunity cost—to the extent that they exist, millions of people are being deprived of benefits in terms of additional health services and/or lower PhilHealth premiums.[16]

Punishing PhilHealth for managerial inefficiency by removing its subsidy and expropriating money from its reserve fund will not make PhilHealth do its job properly. It penalizes the general populace by further reducing the possibility of obtaining more benefits, instead of holding PhilHealth management accountable for inadequate benefits. What is needed instead is to establish an institutional structure that incentivizes efficiency at PhilHealth. Perhaps the PhilHealth charter should be amended to legally define measurable targets in terms of the fulfillment of its mandate of universal health coverage, specifying a cap on the backlog of unpaid hospitals and doctors' allowances at any time, and ensuring these be resolved by a certain date. Additionally, there should be an appropriation to create a professional and competent actuarial unit within PhilHealth, a clearer definition of "reserve fund", with the proviso that if the targets are not met by the specified dates, or if PhilHealth underperforms, the management and board will be replaced.[17]

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[14] However, even if new hospitals are built there, this is an impossible task given the dearth of medical personnel to serve in areas outside the National Capital Region and major urban centers.

[15] This is based on the statements presented by Solicitor General Menardo Guevara and OGCC Head Solomon Hermosura at a preliminary hearing at the Supreme Court on February 4, 2025 of cases filed there on the legality of this expropriation of PhilHealth funds.

[16] At the same hearing, an economist serving as *amicus curiae* to the Supreme Court on this case, Dr. Orville Solon, noted that except for five years, PhilHealth in the last 30 years has always had unused funds in that the amount of contributions far exceeded the benefits paid out by PhilHealth.

[17] This is similar to the tenure of the central bank governor in New Zealand being tied to the attainment of inflation targets. A new PhilHealth President was recently appointed.

Currently, bonuses and perks of PhilHealth staff are drawn from the corporate budget, creating a perverse incentive structure that favors generating "surpluses" or excess funds for PhilHealth employees at the expense of member benefits.

Example no. 3 The Nationally Defined Contribution (NDC) to the Paris Agreement

While the Philippines is among the top five in the weather-related Long-term Climate Risk Index and in the top three in the World Risk Index, the country has an insignificant carbon footprint, emitting only 0.48 percent of global greenhouse gases (GHGs). Nonetheless, the Philippines committed to reduce and avoid GHG emissions by 75 percent for the period 2020-2030 relative to Business-as-Usual (BAU), and to try to peak emissions by 2030.

To begin with, the NDC does not seem to be well-aligned with the national climate change policy articulated in the 2009 National Climate Change Act (NCCA) and its instruments, the National Framework Strategy on Climate Change (NFCC) 2010-2022 and the National Climate Change Action Plan (NCCAP) 2011-2028 [Monsod et al. 2021:2]. The NCCAP has climate change adaptation as the anchor, with mitigation dependent on adaptation and is a by-product of it.

What has happened instead is that the NDC has prioritized mitigation over climate change adaptation and set a target for emissions reduction. This makes little sense in a country with a low carbon footprint, but which is highly vulnerable to climate change risk.

The item Forests and Land Use (FOLU), for example, was removed under Agriculture because forests are negative GHG emitters. But forests are more than just carbon sinks. Forests prevent flooding and soil erosion, and help preserve biodiversity. Because of the emission focus and neglect of the important role of forests in climate change adaptation and mitigation, spending priorities are misplaced, and the effects of climate change are not properly addressed.

Monsod [2022:2, 5-6] questions how the NDC was formulated as the numbers do not add up, the pathways are unknown, and the government is unconditionally committed to a puny 2.71 percentage point of the 75 percent commitment or about 4 percent of the commitment target as of April 2021. Monsod et al. [2021] earlier noted that estimates of potential emissions reduction discussed during a February 2021 consultation with stakeholders only produced an 11 percent reduction relative to the BAU scenario, shown in Table 3. There was no indication as to where the balance of the 64 percentage-point reduction would come from.

One criticism of the NDC is that it is not well-aligned with the National Climate Change Budget, known as CCET. Monsod et al. [2021:3] examine expenditures tagged by the National Climate Change Expenditure Tagging System (NCET) under the CCET, to determine whether they aligned with the country's NDC to the Paris Agreement.

TABLE 3. NDC estimates as of 31 January 2021

Sector	Cumulative GHG emissions (MTCO2e) 2020 to 2030				
	BAU**	Projected reduction/ avoidance		Unconditional	Conditional
		Total	Percent of sector BAU		
Agriculture	539.09	158.3	29.4	0.0	158.3
Waste	286.09	64.9	22.7	8.0	56.9
IPPU (+WHR)	279.84	53.9	19.3	13.9	40.0
Transport	689.19	44.5	6.5	44.5	0.0
FOLU	-113.42				
Energy	1,659.52	45.9	2.8	25.1	20.8
TOTAL	3,340.31	367.5		91.4	276.1
Percent of total BAU		11 percent		2.74 percent	8.27 percent

Source: Monsod [2022:13] based on a DENR presentation on February 3, 2021

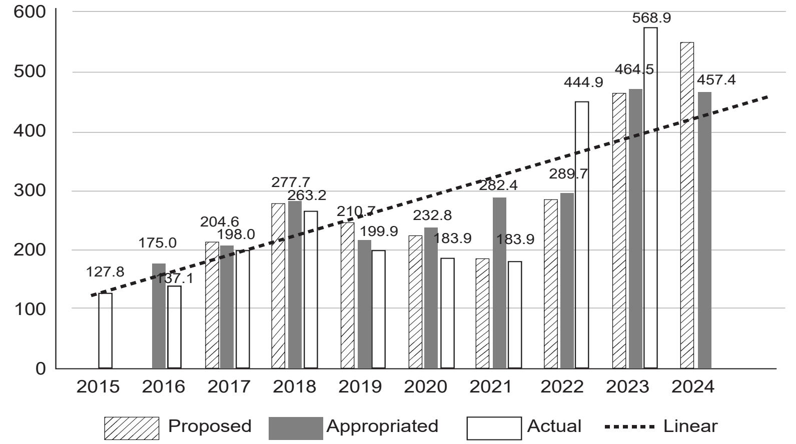
One important data point shown in Table 3 is the zero percent unconditional commitment to reduce emissions in agriculture, which is the second highest source of GHG emissions in the Philippines after the energy sector. Conditional commitment means that the government will delay addressing emissions in agriculture until it receives the technical and financial assistance to do so.

The amount of actual public spending on climate change-tagged expenditures between FY 2015 to 2024, shown in Figure 13, had always been less than the proposed amount and the appropriated amount prior to 2022. In fiscal years 2022 and 2023, actual expenditures for climate change exceeded proposed amounts. From ₱175 billion in 2016, the absolute level of appropriations increased by 161 percent to ₱457.4 billion in 2024, with a sharp increase between 2022 and 2023 of 60.3 percent, equivalent to ₱178.4 billion [Monsod 2024:6].

However, 98 percent of the increase in public spending on climate change between 2022 and 2023 was due to only two agencies, DPWH and DOTr, whose incremental climate change budgets rose by ₱146 billion and ₱24 billion, respectively [Monsod 2024:1]. Meanwhile, the climate change expenditures of key government agencies such as the DENR declined or were underutilized, such as at the Department of Agriculture (DA), in the period 2015 to 2024 [Monsod 2024:8].

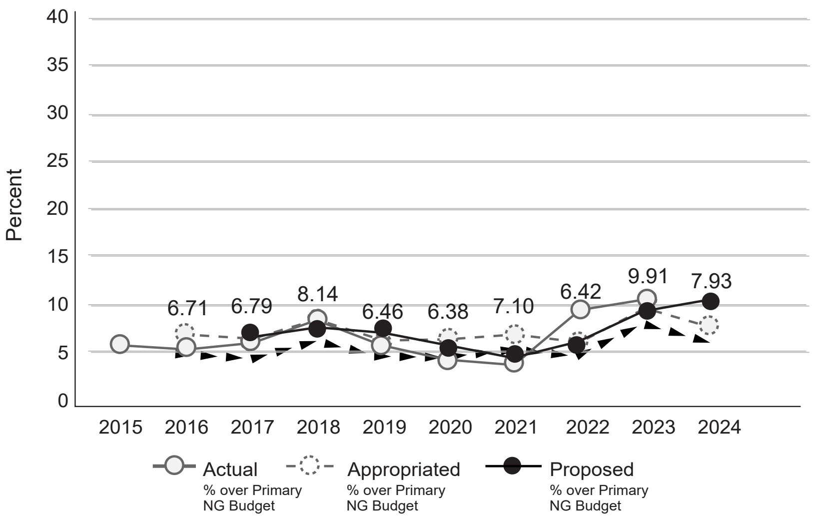
Moreover, these amounts are consistently low as a share of the national budget. Monsod [2024:7], for example, finds that over the period 2016 to 2024, the average share of climate change expenditures in the national budget was only 7.3 percent, shown in Figure 14, and has never exceeded ten percent.

FIGURE 13. Climate change expenditures FY 2015 to 2024 (in ₱ billions, nominal)



Source: Monsod [2024:6].

FIGURE 14. Climate change expenditures as a percentage of the proposed, appropriated, and obligated primary budget, FY 2016 to 2024



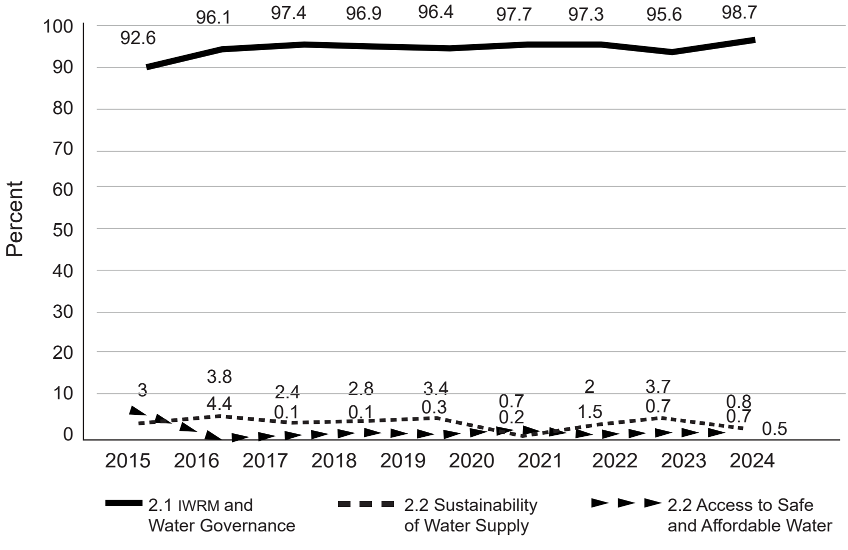
Source: Monsod [2024:7] based on the same data as that in Figure 13

Of the seven Strategic Priority areas in the NCCAP, Water Sufficiency had the highest share of the National Climate Budget (NCB) since 2016, averaging 76.9 percent and 81.6 percent of the NCB in 2023 in 2024, respectively, or an average share of 63.9 percent from 2016 to 2024 [Monsod 2024:10]. Sustainable Energy is the priority with the next highest share of the NCB, but it pales in comparison with only a four percent share of the NCB in 2024 and an average share of 15.6 percent since 2016. Water Sufficiency and Sustainable Energy accounted for almost 80 percent of the NCB from 2016 to 2024. Except for Food Security, which had an average share of 9.2 percent, the rest of the priority areas had an average share of four percent or less in the same period.

Government departments appear to lack the capacity to craft and implement the Programs and Plans (PAPs) required to address climate change in their budgets. A lead agency or several lead agencies are assigned to specific priority areas in the NCB. The lead agency or agencies then tag or identify climate change expenditures in their PAPs for their specific priority area(s) in the NCB.

But oftentimes, there is improper tagging of climate change expenditures in departmental budgets. In some cases, the lead agency for a specific priority area in the NCB is not the lead agency for it, while the non-lead agency tags the expenditure under its climate change PAP. Monsod [2021:5] for example, points out that the Department of Agriculture (DA) did not tag a PAP for Ecosystem and Environmental Stability Strategic (EES) Priority in the National Climate Budget (NCB) even as it is the lead agency for EES.

FIGURE 15. Breakdown of the water sufficiency climate budget by outcome area, FY 2016 to FY 2024 (in percent)

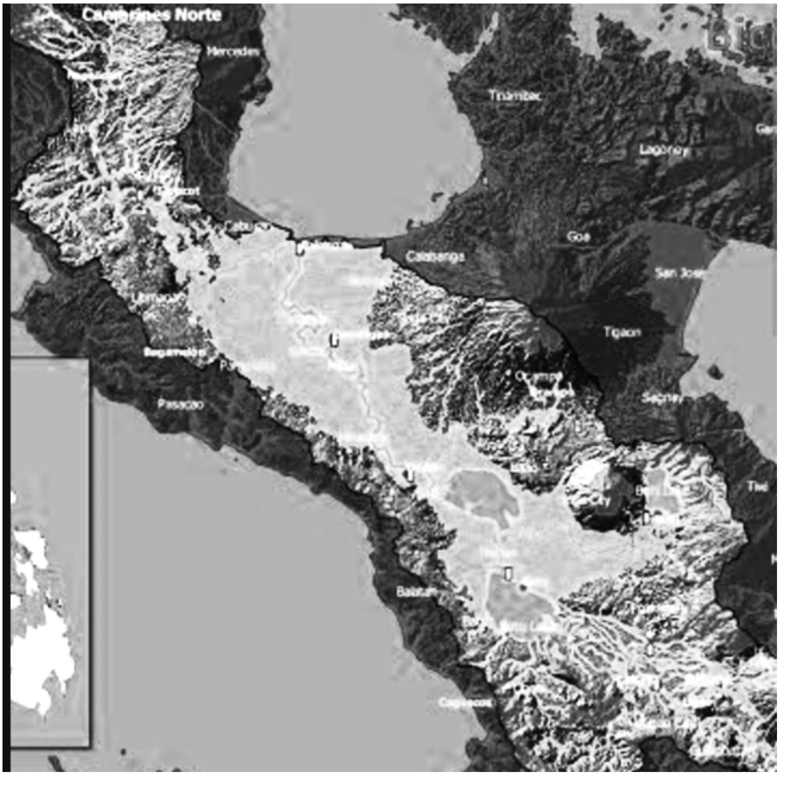


Source: Monsod [2024:12].

Instead, non-lead agencies tag significant amounts in priority areas not under them. For example, 88 percent of the Sustainable Energy (SE) budget went to the DPWH, which is not the lead agency for SE, for infrastructure projects such as the rehab, reconstruction, and upgrading of roads. The DOE, DPST, and DENR, the lead agencies for the SE priority, meanwhile, did not tag any PAPs to support energy infrastructure for climate resiliency. Again, this obvious preference for infrastructure projects, particularly those under the DPWH, appears to be consistent with suspicions regarding rent-seeking opportunities available to members of Congress, especially those with ties to contractors or are contractors themselves.

Figure 15 shows that the large share of 98.7 percent of the Water Sufficiency climate budget in 2024 went to only one item, namely, Integrated Water Resource Management (IWRM) and Water Governance. These are primarily related to flood control infrastructure projects, a favorite infrastructure project of Congress. Meanwhile, access to safe and affordable water and sustainability of water supply—both very important goals, especially for the poor who cannot afford to pay high prices, and for the populace's health—had almost nil or puny shares of the Water Sufficiency Climate Budget.

FIGURE 16. Deforestation of basin and range geomorphology



Source: Private Filipino and Japanese Group of Geologists

In sum, actual expenditures for climate change increased under the Marcos Jr. administration beginning in 2022. However, the share of climate change expenditures in the GAA remains low at under ten percent. Moreover, most of the increase in climate change expenditures is accounted for by only two agencies, with the vast majority of spending allotted to the Water Sufficiency priority area, specifically to flood control infrastructure, whose aggregate share of the budget for Water Sufficiency in 2024 is a staggering 98.7 percent.[18] Departments cannot correctly align PAPs with their budgets. Water Sufficiency and Sustainable Energy PAPs are tagged by departments like the DPWH, which is not even the lead agency for these areas. Outcome areas under the two priority areas, Water Sufficiency and Sustainable Energy, such as access to safe and affordable water, or renewable energy and energy efficiency to lower the cost of electricity, which are of critical importance to the poor, are still inadequately provided by the government.

It is notable that the overwhelming flooding in the Bicol River Basin area during Typhoon Kristine, for example, occurred despite over 98.7 percent of the budget for Water Security being spent on flood control projects of the DPWH. The root cause of unprecedented flooding appears to be the denudation of forests around the Basin rather than the lack of flood control infrastructure. This extensive deforestation area is indicated in black in Figure 16 surrounding the flooded area indicated by the light gray area at the center of the map.[19]

5. Conclusion

It is evident that the government needs to, but has been unable to, make sufficient investments in certain critical public goods for at least the last three decades. Even when there have been dramatic increases in the nominal amount of government spending in areas such as climate change readiness, the share of the national budget going to the provision of public goods, climate change adaptation, and healthcare, in particular, remains low at under ten percent. Aside from underinvestment, the government has prioritized spending on physical infrastructure, such as hospitals, roads, and flood control projects, rather than removing the institutional barriers that constrain the provision of quality healthcare and climate change adaptation. For example, instead of building hospitals to serve low-income individuals in remote areas, investing in technology to enhance operational systems at PhilHealth may be a better way to make quality healthcare accessible to the population, especially the poor. Regarding climate change adaptation, instead of constructing additional physical shelters and evacuation centers, reviewing the prioritization and funding allocation for the different items under the Priority Areas may lead to more beneficial outcomes. In particular, low agricultural productivity needs to be addressed to ensure food security and to protect livelihoods. In general, the government needs to invest in building a better scientific community in the country. Such an effort should start at the basic education level.

[18] According to an article using publicly available data from the DPWH website, a significant chunk of SCDC's (associated with Congressman Co) projects in Bicol went to flood control infrastructure. See de Leon and Valmonte [2025].

[19] Some of these flood control infrastructure projects have been alleged to be 'ghost' projects as well. In some cases, these projects were supposed to be put up in areas which are not known to be flood prone.

The bias in favor of physical infrastructure appears to be related to the incentives for rent-seeking activities created by such projects. This is a major hurdle that needs to be overcome if the Philippines is to accelerate and sustain high growth rates to not only make up for the missed opportunities in the past and the effects of shocks and crises that have held it back and put it on a level field vis-à-vis its neighbors, but more importantly, to realize the goal of becoming a prosperous country with sustainable growth and inclusivity.

Overcoming this hurdle requires a change in the incentive structure in key institutions. There should be a reduction in potential conflict of interest situations and opportunities for rent-seeking. There needs to be greater accountability and competence among public officials. One way to accomplish this would be to tie the tenure of appointed officials to meeting certain targets for their deliverables and to make government processes more transparent by requiring disclosure of the meeting of targets. Elected officials ought to be voted out of office if they are unable to deliver. In both cases, a well-informed and vigilant populace that demands efficient and quality public goods and services from the government and is unwilling to accept the banal tokens of generosity or good governance, is key.

Note: This paper is a revised version of a paper presented at the ANU Philippines Update Conference held at ANU in Canberra on October 31, 2024.

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