NOVAT PUGO SAMBODO

Towards Greater Health Coverage in Indonesia

An evaluation of National Health Insurance (JKN) reform and healthcare use and equity

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Novat Pugo Sambodo

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Towards Greater Health Coverage in Indonesia

An evaluation of National Health Insurance (JKN) reform and healthcare use and equity

Op weg naar een grotere gezondheidszorgdekking in Indonesië

Een evaluatie van de hervorming van de Nationale Ziektekostenverzekering (JKN) en de ongelijkheid in het gebruik van gezondheidszorg

Thesis

to obtain the degree of Doctor from the

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Erasmus University Rotterdam

Doctoral Committee:

Promotors:	Prof.dr. E.K.A. van Doorslaer Prof.dr. M.P. Pradhan
Other members:	Dr. M. Rieger Prof.dr. W. Janssens Prof.dr. L. Trisnantoro
Co-promotor:	Dr. R.A. Sparrow

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CHAPTER 1

Introduction

Health insurance coverage constitutes a pivotal element within a nation's healthcare framework, representing a foundational investment in a country's human capital and economic infrastructure. Suboptimal health conditions can significantly hinder a nation's ability to fully harness its economic potential by disrupting its citizens' capacity for both education and workforce participation (WHO, 2022). The importance of health coverage is multifaceted. First, good health coverage will support positive health outcomes for individuals and communities (American Health Association, 2019). Individuals or households with health insurance are more likely to access early check-ups (Al-Hanawi et al., 2020) and medication (Ungar & Ariely, 2005) compared to those without one. This could help them to improve their health outcomes.

Secondly, having insurance may induce people to use modern healthcare facilities and seek care from skilled healthcare professionals. This is relevant for LMICs with both low antenatal visits and skilled birth attendance. It could also encourage them to get access to modern treatment and drugs, notably in LMICs, where traditional care plays an important part in caring for the sick (Pengpid & Peltzer, 2018; Street et al., 2019). Third, health coverage may help households and communities to reduce financial burdens due to illness (Peng & Zhu, 2021). It may also shield people from the financial ramifications of paying for healthcare out of their own pockets, which could force them into poverty as a result of unexpected illness. Catastrophic health incidents could also force them to spend their entire life savings, exhaust their assets, or take out loans, destroying their futures.

Indonesia, an emerging country with a population exceeding 270 million, has faced the challenge of a substantial portion of its population remaining uninsured, accounting for 45.5% of the total population in 2012 (Dartanto et al., 2016; Fuady, 2019). In response to this persisting challenge, Indonesia introduced the National Health Insurance system (*Jaminan Kesehatan Nasional* or JKN) in 2014. The Indonesian government has pursued integration by consolidating various previous health insurance types, including the introduction of voluntary health insurance in JKN. The government of Indonesia established BPJS Kesehatan (Social Security Agency for the Health sector) as a single pool of healthcare financing funds with the aim of reaching universal health coverage (UHC) by 2019. In this context, and considering the substantial size of the Indonesian population, the reforms undertaken in Indonesia bear high policy relevance for the rest of the world. UHC stands as a prominent goal on the global health policy agenda, embraced as one of the Sustainable Development Goals (WHO, 2015b).

After five years of implementing JKN, Indonesia had not yet achieved UHC, with less than 84% of the population covered, while the target was approximately 95% coverage by 2019 . There still seems to be a definite need for reforms as numerous challenges persist in implementing UHC. These reforms might involve expanding coverage within the informal sector, reducing inequities in access stemming from significant geographical and socioeconomic disparities, reforming healthcare financing, and addressing unforeseen natural disasters.

This PhD research aims to contribute to an evidence-based evaluation of the association and impact of expanded healthcare coverage on health equity and healthcare utilization in Indonesia. Our study has the following objectives:

1. To provide an overview of the JKN program and identify the problems that still exist even after the changes it has brought. We will also estimate the association between district JKN coverage and healthcare utilization as an additional analysis.
2. To assess the healthcare benefit distribution before and after the implementation of JKN using district-weighted healthcare unit cost.
3. To evaluate the effect of reforming the primary care provider payment system for healthcare use in primary care facilities.
4. To assess the impact of forest fires on healthcare use in the affected areas using administrative data.

The second chapter of this thesis assesses the correlation between healthcare utilization and the enhancement of health insurance coverage. We examined the influence of JKN coverage (comprising all types of health insurance) and the share of each type of health insurance on healthcare utilization at the district level. We structured the Indonesian health schemes into four: (1) health insurance for the poor, (2) mandatory health insurance, (3) voluntary health insurance, and (4) private insurance. To achieve this, we analysed *Susenas* 2011-2016 data to explain the relationships in more detail.

Identifying and monitoring access to healthcare benefits among disadvantaged populations is an imperative step for health policymakers. The evidence obtained through this process can play a pivotal role in the progressive realization of universal health coverage (UHC) (WHO, 2023). In response to this, the third chapter of this thesis analyzes trends in healthcare benefit equity among different socioeconomic groups in different geographical locations. We exploited the combination of data from Susenas 2015-2017 and district-level BPJS Kesehatan claims for the same years to assess the distribution of healthcare benefits. Data on BPJS Kesehatan claims at the district level for 2015-2017 contains records of hospital claims and utilization, as well as and the distribution of capitation funds within the district. These data were helpful for constructing district healthcare unit costs and making comparisons between districts. This district-weighed unit cost was incorporated into the Benefit Incidence Analysis (BIA) approach to analyse the JKN benefit distribution (McIntyre & Ataguba, 2011). Our contribution to the literature in this chapter is that we examined the influence of geographical variation in unit costs, a factor that conventional benefit incidence analysis did not consider.

The fourth chapter shows the impact of a major primary healthcare financing change (from capitation to the introduction of performance-based capitation) on healthcare use. The focus is on community health centres or *Pusat Kesehatan Masyarakat* (*Puskesmas*). Primary health care focus is a crucial component of supporting UHC (Hone et al., 2018), which also applies to Indonesia. The puskesmas, located in every sub-district in Indonesia, are supposed to contribute to a better outreach to the general population of Indonesia. A well-designed provider payment mechanism may encourage providers to improve the quantity and quality of their service delivery. BPJS Kesehatan introduced Performance-Based Capitation or *Kapitasi Berbasis Kinerja* (KBK) to improve the quality of service delivery in community health centres (puskesmas). KBK is a capitation payment system that links actual payments to primary care providers to three selected outcomes: contact rate, chronic patient contact rate, and hospital referral rate. Greater utilization of primary healthcare services in Puskesmas is seen as beneficial in the JKN system to the extent that it helps alleviate the hospital burden. The reform started in August 2015 and was rolled out nationally in 2018.

We assessed the implementation of performance-based capitation on healthcare utilization in community health centers (puskesmas) using data from a 1% sample of individuals registered in JKN. This BPJS Kesehatan sample included healthcare usage information for almost 1.7 million JKN members from January 2015 to December 2016 (Fuad, 2019). We used a standard difference in difference specification to estimate the impact on the three relevant incentivized outcomes: contact rate, chronic disease rate, and non-specialist referral rate.

Indonesia is prone to natural disasters, i.e. floods, earthquakes, volcanic eruptions, tsunamis, and forest fires (National Disaster Management Agency (BNPB), 2015). Natural disasters can result in significant loss of life and well-being suffering. They can also cause widespread disruption of health services as a result of reduced supplies during a time of increasing need, resulting in shortages of medicines and other vital equipment. Furthermore, the functioning of the health system may be significantly hampered due to electricity and water shortages or outages. Natural crises can thus severely impede UHC and may destroy years of developmental gains in the health sector (Alwan, 2013).

The fifth chapter of our study delves into the impact of the Indonesian forest fires that occurred from July to October 2015 on healthcare utilization in the affected districts in Sumatra and Kalimantan. Our findings may add some valuable insights to the existing literature concerning the influence of forest fires on healthcare use. We employed district-monthly aggregate healthcare utilization data from BPJS Kesehatan. These administrative data enabled us to capture all records of healthcare use during forest fires. Our focus was on healthcare utilization for all diseases, respiratory diseases, common cold, and acute respiratory tract infection (ARTI) as the main outcomes. Our analysis concentrated solely on the affected islands of Sumatra and Kalimantan. The findings presented in this chapter may provide insights that can inform Indonesian policymakers to protect the most vulnerable groups and areas during forest fires.

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CHAPTER 2

The Indonesian National Health Insurance (Jaminan Kesehatan Nasional) coverage and healthcare utilization

Abstract

The Indonesian Government first implemented a national health insurance system named *Jaminan Kesehatan Nasional* (JKN) in 2014. This system consolidates existing health insurance programs and introduces self-enrolment options to cover non-poor informal sector workers. The main aim of this major healthcare reform is to enhance health insurance coverage to foster greater accessibility to healthcare for the Indonesian population. Our first objective is to provide an overview of JKN implementation and persisting problems within the system. Our second objective is to examine the correlation between the increasing share of coverage and healthcare utilization at district level. Utilizing a district and year fixed-effect approach with six years of district-panel data spanning 2011−2016 (sourced from nationally representative socio-economic data), we observed a general upward trend in health insurance coverage in Indonesia following the implementation of JKN. Our results suggest that JKN implementation results in a strengthened positive association between healthcare insurance coverage and utilization, particularly in hospital care. This suggests that the new health insurance scheme promotes the use of hospital care. We expected that the role of the referral system under JKN would also increase outpatient primary care use. However, this was not apparent from the results. Moreover, in spite of the enhanced opportunities for JKN-covered individuals to also use private facilities, we do not find a statistically significant association between private care use and insurance coverage among the (subsidized enrolled) poor and (mandatory enrolled) formal sector. This suggests that JKN coverage is not associated with greater use of private facilities. Furthermore, the increasing use of public care demands attention as Indonesia tackles the bottleneck in public hospital access. Self-enrolled insurance in the informal sector exhibits the strongest positive correlation with hospital care utilization compared with subsidized and mandatory schemes. This signals that an important degree of adverse selection seems to be occurring, posing a potential threat to JKN's financial sustainability.

2.1. Introduction

Indonesia, one of the most populous countries in Southeast Asia (with a population of 270 million), is facing a healthcare coverage challenge. In the early 2000s, a significant portion of its vast population lacked access to formal health insurance (Rokx et al., 2009). Health insurance coverage was primarily available to civil servants and formal sector workers, leaving those in the informal sector without insurance protection. This fragmentation in health insurance coverage created multiple barriers to accessing healthcare services for those in the informal sector.

The consequences of this fragmented healthcare landscape were twofold. First, it resulted in marked inequities in the availability and quality of healthcare services across the population. Second, this led to a dependence on out-of-pocket medical spending, accounting for approximately 34.76 percent of the total healthcare expenditure in 2019. This figure significantly exceeds the World Health Organization's recommended threshold of a maximum of 20 percent (Prasetya & Afrina, 2022). This prevailing practice of out-of-pocket spending placed a substantial financial burden on individuals and families, making access to healthcare services unaffordable for many. Furthermore, the increased burden of non-communicable diseases (related to income growth, and lifestyle and nutrition changes) is associated with higher healthcare costs (Purnamasari, 2018). These financial vulnerabilities pose a significant challenge to the overall health and well-being of individuals and families in Indonesia.

The Indonesian government has set a goal to ensure that the entire population of Indonesia receives healthcare and health insurance for the basic health needs. This objective aligns with Indonesian Law Number 40 of 2004 on the National Social Insurance System (Government of the Republic of Indonesia, 2012) and other regulation products (see Appendix Table A1). This accords with the broader objective of achieving global universal health coverage (UHC), which is to prevent all citizens from suffering catastrophic health spending (WHO, 2015a). To attain this goal, Indonesia implements a national health insurance system called *Jaminan Kesehatan Nasional* (JKN).

The main aim of JKN is to consolidate all existing formal health insurance schemes into one single-payer system. In addition to merging the pre-existing health insurance schemes, JKN has incorporated the informal sector non-poor as self-enroled members. The reason for implementing this policy is that the healthcare schemes in place before 2004 remained fragmented, leading to difficulties in managing healthcare costs and ensuring service quality (Ministry of Health, 2014). By consolidating these existing schemes, JKN could cover around

58.5% of the total population in 2014. Two years later this reform increased insurance coverage in Indonesia that grew to 65.6% in 2016. Most of the increase came from health insurance for the poor and the self-enrolled categories by additional 24 million and 15 million enrolees, respectively (see Appendix Table A2) (Fuady, 2019). The growth of the subsidized Health Insurance for the Poor (HIFP) is driven by the expansion of the Indonesian government's social security initiatives. In contrast, self-enrolled individuals predominantly consist of non-poor informal sector workers seeking healthcare coverage. However, it is worth noting that total enrolment still falls short of the intended target.

The primary objectives of this paper are to provide an overview of JKN implementation in Indonesia and to describe the persisting problems that remain unsolved despite the introduction of JKN. In addition, we also aim to explore the relationship between JKN membership (and membership of any insurance scheme) and healthcare use at district level in Indonesia.

The subsequent parts of this chapter provide a brief introduction to JKN evolution and the remaining problems with JKN. Section 2 describes the existing literature on this topic and the research objectives. Section 3 outlines some characteristics of the data used in this research. Section 4 explains the method of this research. Section 5 discusses the results of this study and the detailed discussion regarding findings of this research as well as its limitations. Lastly, section 6 states the main conclusion of this research.

Indonesian National Health Insurance (*Jaminan Kesehatan Nasional*) Reform

JKN Evolution

JKN consolidates membership from the existing social health insurance schemes and introduces self-participatory health insurance with contributory premiums, specifically targeting the non-poor informal sector (Mboi, 2015). In this section, we will briefly explain how the previous schemes were established and how they have been incorporated into the JKN system.

In Indonesia, health insurance has undergone several significant changes. In 1968, the Indonesian government established *Badan Penyelenggara Dana Pemeliharaan Kesehatan* (BPDK or the Agency for Healthcare Funds), which managed *Dana Sehat* (the Health Fund) under the Ministry of Health. The *Dana Sehat* program operated as a non-profit initiative with a primary focus on providing health insurance for the poor. After 16 years, BPDK was transformed into *Perum Husada Bakti* (PHB), which became a state-owned enterprise with a profit motive. It managed health insurance programs for both the public and the formal and private sectors.

In 1984, *Asuransi Kesehatan* (Askes) was established, replacing PHB. Askes played a pivotal role in managing the civil servant or public formal sector and served as the precursor to *Badan Penyelenggara Jaminan Kesehatan* (BPJS Kesehatan), which was introduced in 2014. Indonesia also introduced a workers' insurance program known as *Jaminan Sosial Tenaga Kerja* (Jamsostek) for the private formal sector. For the military, police, and Ministry of Defense personnel, Indonesia established ASABRI in 1971 to cater to the unique needs of the defense sector (ASABRI, 2016).

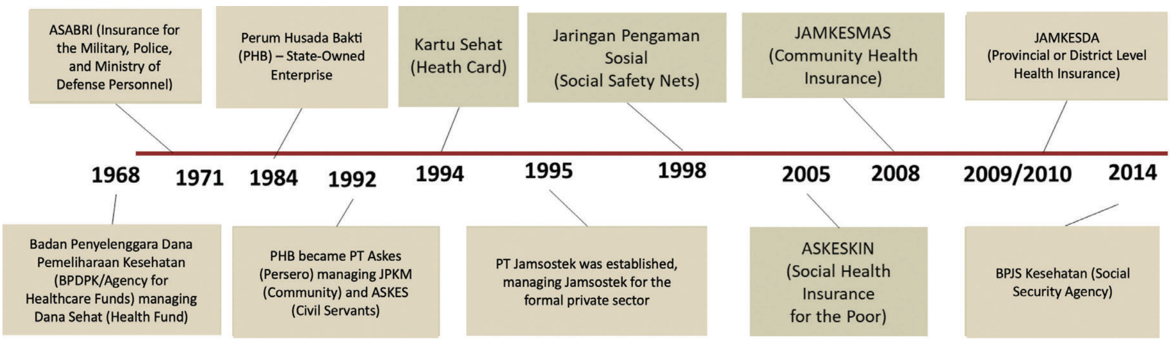
Improvement of healthcare access for the poor was addressed on a national scale as part of a social safety net in response to the fallout of the financial crisis of 1998 (Rokx et al., 2009). Poor households were given access to a health card program, which waived the fees for the use of services provided by public hospitals and community health centers (*Puskesmas*). The goal was to shield the underprivileged from the Asian Financial Crisis of 1997–1998's economic upheaval. The vulnerability of the poor had been exacerbated during the crisis due to various factors, including a significant decline in employment rates, high inflation, and an ongoing socio-political crisis.

In 2005 the Government of Indonesia (GoI) attempted to reform the social health insurance by broadening the group of beneficiaries. The government introduced health insurance for the poor (*Asuransi Kesehatan untuk Keluarga Miskin* – Askeskin) with the goal to expand the coverage to the poor informal sector workers that had not been covered by the existing insurances. The basic idea was to mimic Askes but for the poor. Afterward, GoI appointed the Ministry of Health to manage the financial aspect of Askeskin because there had been many requests for evaluation and improvement. It was then renamed Jamkesmas in 2008. In this program, the near poor group was included as eligible recipients. The chronological detail on this evolution can be seen in Vidyattama et al. (2014) and Dartanto et al. (2016) (Figure 1).

A significant change brought about by the introduction of JKN in 2014 was the inclusion of non-poor informal sector workers into the JKN system through voluntary membership in BPJS Kesehatan. This group was mostly neglected by the schemes before JKN. The objective of the reform is offering a breakthrough increase coverage for the so-called “missing middle”, which pertains to individuals who are non-poor and employed in the informal sector but are left without health coverage from either subsidized programs for the poor or mandatory insurance for the formal sector (Dartanto et al., 2016). It presents a considerable challenge, given that this non-poor informal sector group constituted approximately 57.75 percent of the population in 2015 (Badan Pusat Statistik (BPS), 2018).

The introduction of this scheme is one of the consequences of the solidarity principle of JKN, which mandates that all Indonesians must participate in the system. However, this scheme also brings a huge financial burden to the system. The non-poor informal sector, often not subject to taxation, contributes little to the Indonesian government's fiscal resources (Witoelar & Utomo, 2023). Moreover, BPJS Kesehatan cannot enforce premiums for this sector due to the absence of supporting regulations, and such enforcement may not be politically viable. This condition incentivizes informalization and potentially leads to a huge financial gap in the overall program.

Figure 1. Evolution of Health Insurance in Indonesia



Source: Author’s illustration based on Askes (2014), Vidyatama et al. (2014), and Dartanto (2016).

JKN membership

BPJS Kesehatan membership can be categorized into two main groups, each representing distinct methods of premium contribution payment and premium amounts (Dartanto et al., 2020). The first category comprises non-contributing members (*Penerima Bantuan Iuran*, abbreviated as PBI) and is considered as HIFP, which is designed to provide coverage for the poor, near-poor, and other similar groups who are unable to pay their insurance premiums regularly. The government covers the monthly premiums for BPJS Kesehatan, making a payment of IDR 23,000 (approximately USD 2) per person per month through the Ministry of Finance. This HIFP category primarily comprises former Jamkesmas members, along with some additional eligible individuals identified based on the standardized criteria. It is important to note that -- unlike Jamkesmas -- the membership of Jaminan Kesehatan Daerah (Jamkesda) or a local government (provincial or district level) health insurance program cannot be automatically transferred to the non-contributing membership category. This distinction arises from the fact that Jamkesda offers different packages and payment schemes, and is managed by local governments at district or provincial level. As a result, former Jamkesda members are required to visit the nearest BPJS office for verification in the early phase of JKN implementation.

The second category consists of contributing members, or non-PBI, and encompasses three distinct groups. The first one is wage-recipient members working in the formal sector, which include individuals from both the formal private and formal public sectors (formerly known as Askes and Jamsostek for Health). Their premiums are deducted at approximately 5% of their salary in this category (1% from the employee and 4% from their employer). The second group is non-wage recipient members working in the informal sector (self-enrolled/voluntary health insurance). In 2014, this group was required to pay a monthly premium, with the amount ranging from IDR 25,500 to 80,000 (USD 2 to 5) per household member, depending on the ward class they chose. In 2019, this premium was increased to the range of IDR 42,000 to 160,000 (USD 3 to 10) or an increase of around 100% (Biro KLI Kemenkeu, 2019). The last group consists of pensioners, including former government officials, military personnel, employees of the formal sector, and veterans (Mandatory Health Insurance). These pension beneficiaries do not make the premium payments themselves; 5% of their pension fund covers these costs (1% from the employee and 4% from the employer). Family members are automatically included as members of these groups.

Table 1. Classification of Health Schemes for Our Analysis

	Prior to JKN (Before 2014)	After JKN (2014−Present)
Health insurance for the poor (HIFP)	*Dana Sehat, Jaminan Pemeliharaan Kesehatan (JPK), Askeskin, Jamkesmas, Jamkesda*	*Penerima Bantuan Iuran* (PBI) – Non-contributory category
Mandatory health insurance for the formal sector (MHI)	Askes, ASABRI, Jamsostek, and private insurance	*Pekerja Penerima Upah (*PPU) – Contributory category – Formal (Public and Private)
Self-enrolled health insurance for the non-poor informal sector (SEHI)	Did not exist	*Pekerja Bukan Penerima Upah* (PBPU) – Contributory category – Informal

For our analysis, we construct four groups of health insurance cover that have the same characteristics of beneficiaries before and after the implementation of JKN (Table 1). This study classifies all types of membership into three groups: (1) health insurance for the poor, (2) mandatory health insurance, and (3) self-enrolled health insurance. To maintain consistency over time, we incorporate private health insurance into mandatory health insurance. Private insurance holders, mainly from the private formal sector, can only enrol through the PPU scheme after the implementation of JKN.

JKN Benefits

The JKN program covers a comprehensive healthcare benefit package, including basic and advanced dental health services. The benefit packages are all the same for all categories mentioned in Table 1. The detailed list of healthcare benefits of JKN was originally specified in Regulation of the Minister of Health No. 69 of 2013, and it has been amended three times based on the evaluation of JKN. The latest list is provided in Regulation of the Minister of Health No. 64 of 2016 (Mahendradhata et al., 2017).

The characteristics of healthcare services covered in the JKN system are promotive, preventive, curative, and rehabilitative; it also includes pharmaceuticals. However, the curative care accounts for most of the BPJS Kesehatan budget. Based on the regulation of the Minister of Health on the JKN benefit package, BPJS Kesehatan provides its members with a comprehensive basic benefit package. Each medical indication dictates the entitled benefits based on the Indonesia Case-Based Group (INA-CBG) code. This covers the outpatient and inpatient care starting from the appointed primary care to the secondary and tertiary care based on a referral. Even though it covers most of the medical treatments, there are some exclusions for a small number of healthcare treatments; BPJS Kesehatan only provides partial coverage through reimbursement for such treatments.

In addition to the coverage for outpatient and inpatient care, BPJS Kesehatan also offers benefits for several health-related types of equipment with value or quantity limit. For example, eyeglasses, hearing aids, and equipment for people with disabilities. This equipment must be acquired from BPJS-registered providers based on the INA-CBG code.

The benefits of BPJS Kesehatan can also be combined with private insurance using the coordination of benefit scheme as a supplement to BPJS Kesehatan. Thus, this can be an option for BPJS Kesehatan members to maximize the coverage of their insurance benefit package. Based on Regulation of the Minister of Health No. 40 of 2012 on guidelines for the implementation of social health insurance, there is no co-payment and an upper limit on the health treatment in the JKN system (Mahendradhata et al., 2017). The co-payment is now allowed with new Health Law No. 17 of 2023.

Remaining problems under the JKN system

Several problems remain, however, and four have been identified in this study. First, the newly created self-enrolled category is a fundamental change to JKN, but it also brings problems to the system's sustainability. The initial procedure of BPJS Kesehatan registration for voluntary membership is prone to adverse selection. Right after successful registration, a member can immediately exploit their insurance benefit. For instance, visiting a listed healthcare provider on the same day to treat their known health condition. This loophole can potentially lead to adverse selection whereby most newly registered members are those in high-risk health conditions while individuals with better health conditions intentionally delay registering for BPJS Kesehatan. Another point to note is that the registration procedure requires no prior health verification. In response to this, Presidential Regulation No. 82 of 2019 mandated that new self-enrolled members had to wait for 14 days for verification before they could be activated for use.

This ease to register without any risk assessment filter and the high unmet healthcare need in this sector have resulted in a significantly higher claim ratio compared to the other beneficiary groups. In 2018, the PBPU/SEHI participant claims ratio soared to 313% with the total PBPU/SEHI participant claims amounting to IDR 27.9 trillion (USD 1.8 billion), while the total contribution collected was a mere IDR 8.9 trillion. The ideal claim ratio is accounted less than 90% (Hukum Online, 2015). In addition, their premium payment rate was also low with only

53.7% in the same year (CNBC, 2019). This may endanger the whole system because the Indonesian government also has a limited source to subsidise the non-poor informal sector workers in the JKN system. This is due to the low tax base in Indonesia that is around 10.7–11.4 percent (OECD Economic, 2016), which limits the space for additional health financing.

Second, the ‘missing middle’ problem for the non-poor informal group persists, even after 9 years of JKN implementation, but fortunately, it is a shrinking middle because the active member share (who paid the premium) is declining (Kompas, 2020). This might be due to this group’s low willingness to pay JKN premiums. Dartanto et al. (2016) evaluated the willingness to pay for participation into JKN of the non-poor informal sector groups. They found that the low participation of poor informal groups is because the single flat rate of the insurance premium is unfair and too expensive. The COVID-19 pandemic also led to a decline in the number of active self-enrolled members (Kompas, 2020). This non-poor informal group coverage was originally intended to be mandatory for JKN registration, with the government planning to impose penalties that could result in the loss of certain benefits for residents who failed to enrol by 2019. However, these penalties have not yet been enforced due to lack of supporting regulations.

Third, the socio-economic and geographic gaps hinder equal access and healthcare benefits (Trisnantoro, 2019). Higher-quality clinics and hospitals are predominantly concentrated in urban areas within Java and Bali. Additionally, a significant number of health specialists are primarily located in these regions. Consequently, the value of JKN membership for residents residing in Java and Bali is considerably higher in comparison to those in regions such as Papua or East Nusa Tenggara (NTT). We address this issue in greater detail in Chapter 3 of the thesis.

Fourth, there has not been any significant improvement in the overall quality of primary healthcare. According to Regulation of the Minister of Health No. 75 of 2014 regarding Community Healthcare Centers (Puskesmas), it was expected that by 2019, a total of 6,000 Puskesmas would be able to provide services in line with the established standards. However, based on the self-assessment reports submitted by Puskesmas in 2017, only 3,225 Puskesmas met the standards or 53% of the 2019 target. This fell short of the target, considering there were 3,392 Puskesmas that had reported to the Ministry of Health. This has raised a significant issue to be addressed as Puskesmas plays a pivotal role in the primary care system in Indonesia, serving as the gatekeeper. The subpar performance of Puskesmas has led to an increased rate of referrals to advanced care facilities, ultimately resulting in bottlenecks in hospitals. These bottlenecks contribute to a decline in service quality and cost inefficiency within the JKN system (Fuady, 2019). The four problems identified above remain a substantial challenge to the success of JKN.

2.2. Evidence from Indonesian JKN

Empirical research on JKN impact

Numerous studies have explored the impact of health insurance coverage expansion on healthcare utilization in various low- and middle-income countries (LMICs). Some relevant models for comparison with Indonesia are its neighboring countries, including the Philippines and Thailand. The Philippines has its national health insurance program, PHIC/PhilHealth, and Thailand implemented its Universal Coverage Scheme (UCS) in 2002 (Tangcharoensathien et al., 2011, 2014). Both PHIC and UCS have demonstrated positive effects on healthcare utilization. Holding PHIC insurance in the Philippines was associated with higher odds of using outpatient care and inpatient care, with increases of 42% and 47%, respectively (Haw et al., 2020). Furthermore, the ownership of UCS in Thailand led to a decrease in non-formal treatment by 3.2 percentage points and an increase in admissions to public hospitals by around 1 percentage point (Limwattananon et al., 2013). The question arises as to whether this success story also unfolds in Indonesia.

Some researchers have investigated the impact of JKN on healthcare among the Indonesian population. Erlangga et al. (2019), for example, found that JKN successfully increased the probability of inpatient admission for the self-enrolled scheme and health insurance for the poor by 8.2% and 1.8%, respectively. Using data from the Indonesian Family Life Survey (IFLS) waves 4 (2007) and 5 (2014), they found that the probability of using outpatient care for the self-enrolled is 7.9% higher than that for the uninsured.

Johar et al. (2018) reported similar results, but they also found that the role of supply is vital for Indonesians accessing healthcare. The effect of insurance ownership is smaller if the location where the individuals live has limited access to healthcare. A similar approach was also adopted by Pratiwi et al. (2021), but their study was conducted at district level by combining data from Susenas (the National Socio-Economic Survey), the National Census of Villages (PODES), the population health development index, and BPJS Kesehatan records in 2018. They found higher use of inpatient care among JKN-insured patients than the uninsured ones.

Some research projects show that maternal care use also increases JKN enrollment (Anindya et al., 2020; Rosidah & Asdary, 2021). Anindya et al. (2020), who used data from the Indonesian

Demographic Health Survey (IDHS), found that JKN enrolment is positively correlated with a higher probability of attending antenatal care 4+ visits (7.4%), skilled birth attendance (3.0%), and prenatal care with skilled providers (4.5%).

Inequalities in healthcare services also declined after JKN implementation, especially for outpatient care in primary care (Mulyanto et al., 2019). JKN has also improved in that it helps the poor with their out-of-pocket payment and healthcare expenditure of its members (Couturier et al., 2022; Nugraheni et al., 2020). Nevertheless, regional discrepancies persist, primarily due to uneven distribution of healthcare facilities, with a concentration in Java and Bali islands (Sambodo et al., 2021).

Previous studies that focus on JKN and healthcare use, have primarily used individual data, and some have used district-level healthcare use. Erlangga et al. (2019), for example, used IFLS 4 and 5 to capture the impact using panel individual data before and after JKN implementation. Using the two waves of IFLS is also subject to a caveat since much of it happened during the period 2007 to early 2015 (7 years). During this time, Jamkesmas and Jamkesda were also introduced. Therefore, some effects would be carried over to the JKN impact estimate. Unlike Erlangga et al. (2019), our study only covers three years after JKN implementation, which provides a more up-to-date view of the correlation between JKN and healthcare utilization. Pratiwi et al. (2021) employed district-level data, but their study solely relied on one-year (cross-sectional) data from 2018. This approach does not seem to be able to capture the changes in JKN both before and after its implementation.

In sum, previous studies have mostly concentrated on either the combination of all health insurance schemes (TNP2K, 2017; Vidyattama et al., 2014) or a single social health insurance scheme, such as Kartu Sehat (Johar, 2010), Askeskin (Sparrow et al., 2013), Jampersal (Achadi et al., 2014), Jamkesmas (World Bank, 2011), and Jamkesda (Sparrow et al., 2016). We aim to add to the the limited regional-level analysis by assessing the association of different beneficiaries' populations but with the same benefit package scheme on healthcare utilization at district level.

From the literature review and the JKN reform described above, we hypothesize four findings. First, we generally expect the increase in general health insurance coverage to be associated with a rise in healthcare use. Second, JKN has a referral system and employs primary care as a gatekeeping mechanism. Therefore, we expect the use of primary care to be more positively associated with new enrolments in JKN. Third, we anticipate a positive association especially for HIFP in using care in both primary care facilities and hospitals, particularly in public facilities because they are more available for them. Fourth, since JKN provides all health insurance holders with the option to choose between private and public providers, the use of private services may slightly increase when the share of the non-poor insured individual schemes (MHI and SEHI) increases, but this is not the case for HIFP because private facilities are less available for its members. Fifth, we expect the positive association between the SEHI scheme share and healthcare use will be larger compared to the other schemes, as its members register and pay premiums themselves.

2.3. Data

Susenas

We used data on health insurance coverage and healthcare utilization from the Indonesian National Socio-Economic Surveys (Susenas) 2011–2013 (pre-JKN) and 2014–2016 (post-JKN). These repeated cross-sections provide nationally representative data on the socio-economic status of households and individuals. The survey was conducted by the Indonesian Statistical Bureau (BPS), and it involved approximately 280 thousand households and 1.1 million individuals. To be nationally representative, BPS provided weighted samples for both household and individual datasets to reflect the actual population of Indonesia. Susenas also contains abundant information on socio-economic and demographic characteristics, including self-reported income, household expenditure, and household assets. It also has information on individual health conditions, but it is somewhat limited. Susenas also covers information on healthcare insurance participation, healthcare service utilization (inpatient and outpatient care), and participation in other social protection programs.

The questions in the 2015–2016 Susenas survey distinguish between the existing health insurance schemes in Indonesia. We classified all types of membership participation into four groups: (1) health insurance for the poor, (2) mandatory health insurance, (3) self-enroled health insurance, and (4) private health insurance (Table 1). Then, we constructed the share in a district for each group by dividing the number of individuals that had each insurance by the total population of the district. This percentage coverage of a district population was used as treatment intensity indicator.

Individual information on outpatient care utilization and inpatient healthcare variables was obtained from Susenas. Using this information, we constructed two primary outcome variables of interest: first, the number of outpatient health visits per 1,000 persons, and second, the number of inpatient care stays per 1,000 persons. The incidence of outpatient care was queried for the last month occurrence, while the incidence of inpatient care was queried for the last year occurrence. The data also contains information about healthcare facilities visited by the respondents. Healthcare providers listed in the survey are public hospitals, private hospitals, *Puskesmas*/*Puskesmas Pembantu* (community health subcenters)/*Polindes* (village midwife clinics)/*Posyandu* (integrated health service posts), GP, policlinics, medical staff (midwives, nurses, and village health practitioners), alternative medications, and traditional medical practitioners (*dukun*). In this research, we excluded visits to alternative and traditional practices in our sample.

We differentiated types of providers based on ownership, i.e. public and private facilities. In the survey, respondents were provided with the seven options above and one open answer to allow them to specify an unlisted healthcare facility. We only distinguished between healthcare utilization in public facilities and that in private facilities. Furthermore, we investigated whether JKN correlated with a user's shift from public to private healthcare services and its distribution.

2.4. Method

Empirical specification

The primary aim of this analysis is to assess the association between JKN membership and healthcare utilization at district level over a six-year period from 2011–2016 using district-level panel data derived from Susenas survey. Assessing the causal impact of JKN posed several challenges in our setting. First, JKN implemented at a country level without a step-by-step approach. Second, enrolment into the health insurance schemes was not random, as different insurance classes were associated with individual characteristics such as sector of employment. For example, individuals from the non-poor informal sector joined the JKN in the SEHI scheme, potentially driven by adverse selection, where riskier individuals and those seeking care are more likely to join JKN and use more care. This would introduce unobserved heterogeneity such as risky behaviour and health knowledge that would be associated with health insurance take-up. Therefore, a simple comparison of health care utilization by insurance coverage is likely to provide biased estimates of the causal effect of JKN on healthcare use.

The Susenas data provides a district panel with which we can employ a district and time (year) fixed effect model to control for time-invariant unit-specific heterogeneity (Millimet & Bellemare, 2023). The identifying assumption for interpreting causal effects with this approach is that, in absence of any health insurance reforms, health care utilization would follow the same trend across districts. The district fixed effects can account for most sources of bias, but adverse selection remains a realistic threat to the parallel trends assumption, especially for voluntary self-enrolment. For that reason, the estimation results need to be interpreted with caution, and as (partial) associations rather than causal relationships.

We defined data from 2011–-2013 as the before JKN period ($Post$=0) and 2014-2016 as the after JKN period ($Post$=1). Self-enrolled (BPJSK PBPU) coverage was set zero (0) for the period 2011-2014 for all districts. The 2014 Susenas survey was conducted in March 2014, during the early implementation of JKN. Therefore, the self-enrolled JKN figure might be near zero between January and March 2014.

The fixed effect model is shown in Equation 1:

$$Y_{it} = \mu_1 HealthInsurance_{it} + \mu_2 HealthInsurance_{it} * Post_t + year_t + \delta_i + \varepsilon_{it} \quad (1)$$

where Y_{it} is our observed outcome of interest, e.g. monthly outpatient admissions per 1,000 persons in the past month and inpatient admissions per 1,000 persons in the past year. We used district total population (including non-healthcare users) as denominator. Variable $Year_t$ reflects the year dummies, and δ_i denotes district fixed effect. $HealthInsurance_{it}$ is the share of the population that has any type of health insurance in district i and year t. μ_1 estimates the strength of relationship between health insurance ownership in a district with healthcare use. The coefficient of the interaction term μ_2 determines how the association between share of health insurance coverage and healthcare use is changed post JKN. For example, if the association was positive before JKN and the interaction term is positive, it suggests that the positive association is strengthened after JKN. Conversely, if the interaction term is negative, it implies a weakening of the positive association post JKN.

Next, we used a breakdown of health insurance ownership into different types using Equation 2:

$$Y_{it} = \beta_1 HIFP_{it} + \beta_2 MHI_{it} + \beta_3 SEHI_{it} + \theta_1 HIFP_{it} * Post_t + \theta_2 MHI_{it} * Post_t + year_t + \delta_i + \varepsilon_{it} \quad (2)$$

The variables $SEHI_{it}$, $HIFP_{it}$ and MHI_{it} capture the percentage of population of a district enrolled in self-enrolled, health insurance for the poor and mandatory health insurance scheme of district i at year t, respectively. The β coefficients refer to the association of health insurance type with healthcare use for each of these types of health insurance schemes, where β_3 denotes the estimate for self-enrolled insurance only after JKN implementation (since it did not yet exist pre-JKN). The explanation of each scheme that is included in pre- and post-JKN is provided in Table 1.

The θ coefficients indicate the strengthened (or weakened) association of coverage with healthcare use post JKN for non-voluntary insurance types MHI and HIFP. A positive θ_2 suggests that a strengthened association may indicate that JKN offers better benefits for the MHI scheme compared to the previous scheme, incentivizing MHI scheme holders to use the service more. In the case of HIFP, a positive and significant coefficient θ_1 suggests that the poor group finds it easier to access healthcare services post JKN. Conversely, a negative sign for θ may indicate the addition of more low-risk individuals into both schemes, making them less likely to use healthcare services.

2.5. Results and Discussion

Descriptive Statistics

The health insurance ownership pattern by type changed gradually during the 6-year period. Figure 2 shows changes in the share of health insurance in two periods: 2011–2013 and 2014–2016. Overall, the graph indicates a consistent decrease in the percentage of uninsured individuals over time, dropping from 47.9% in 2011 to 27.7% in 2016. The “shrinking middle” of uninsured individuals was primarily attributed to the increasing availability of health insurance for the poor, with a notable 11–14% increase in its share between 2013 and 2016, as shown by the shrinking red bar over the period of time in Figure 2. The share of health insurance for the poor remained stable after JKN at around 40%, reflecting the Indonesian government's target of covering 40% of the total population categorized as poor and near-poor population. Some previously uninsured individuals, particularly those in the non-poor informal sector, transitioned to self-enrolled health insurance (the green bar in Figure 2). This shift was shown by the increasing share of the non-poor informal sector (self-enrolled health insurance), which accounted for 6.5% in 2015 and 9.8% in 2016. This increase may suggest that more people were willing to pay BPJS Kesehatan premiums, but the rise was lower than expected. This may be related to the availability of healthcare supply and limited willingness to pay premiums (Khoirunurrofik & Raras, 2021).

The mandatory health insurance maintained a fairly steady rate of around 17–23.6% (the yellow bar) from 2011 to 2016. This figure could be a result of the combined share of public formal (civil servants) and private formal health insurance. This seems to be reasonable because the number of government officials and military members did not contribute much toward the increase in this period. It is important to note that the data in this figure was based on information from March of each year. The absence of self-enrolled health insurance data in 2014 was due to the lack of information provided by Susenas in that year.

In general, healthcare utilization showed a significant rise following the implementation of JKN. Across all types of healthcare services, whether primary or hospital, public or private, district utilization rates increased significantly (Table 2). Increases were observed in outpatient utilization of primary care and public healthcare facilities with an increase of 16.51 and 10.95

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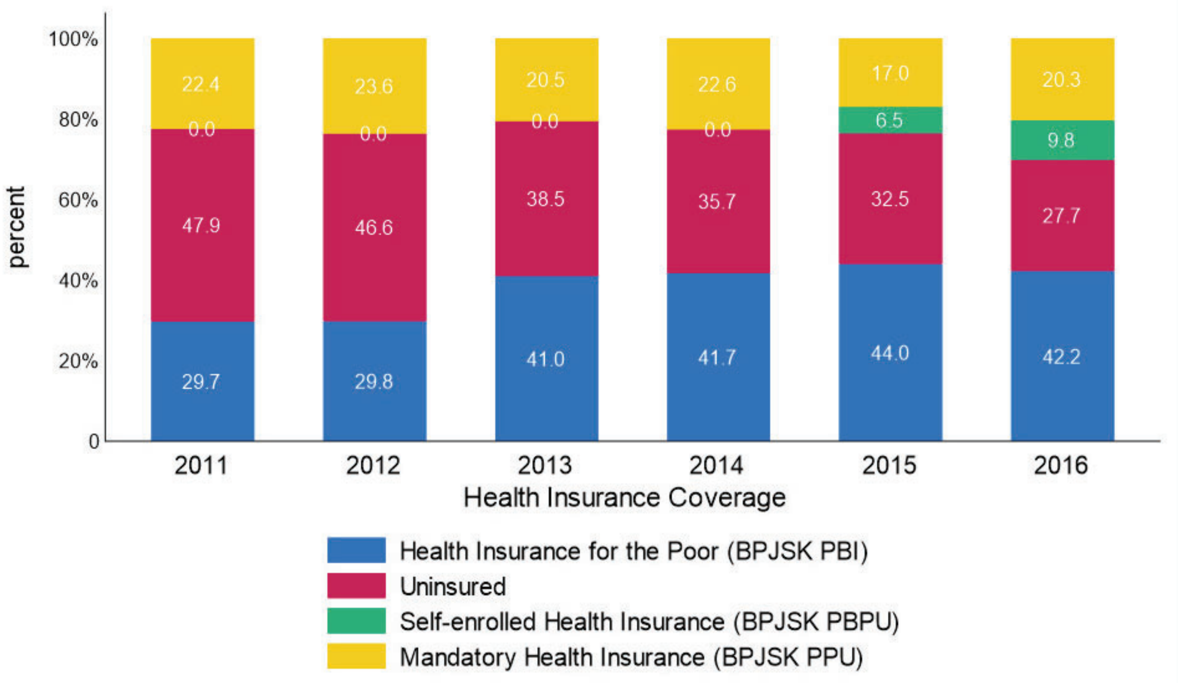
per 1,000 individuals post-JKN, respectively. This suggests that overall the public primary care services were much more accessible to the Indonesian population (Figure 3A).

Furthermore, the relative increase was even greater in hospital admissions, with a rate increase of 11.82 per 1,000 individuals, which effectively doubled the pre-JKN period. The progress in inpatient admissions in private healthcare facilities was particularly encouraging, suggesting that the implementation of JKN did not only benefit public providers (Figure 3B). This trend may indicate that private healthcare facilities were also more receptive to patients enrolled in health insurance for the poor, a scenario less common in the pre-JKN era.

Figure 2. The Percentage of Health Insurance Coverage of the Total Population in Indonesia, 2011–2016



Note: Authors' calculation based on Susenas 2011–2016 data

Table 2. Means of District Characteristics Pre and Post JKN

	Pre-JKN (2011-2013)	Post-JKN (2014-2016)	Post-JKN – Pre-JKN
Healthcare Utilization			
Outpatient			
Outpatient rate (cases per 1,000 population)	120.24	142.81	22.57***
Outpatient primary care facilities	107.94	124.45	16.51***
Outpatient hospitals	11.39	16.53	5.14***
Outpatient public healthcare facilities	57.13	68.08	10.95***
Outpatient private healthcare facilities	68.29	76.17	7.89***
Inpatient			
Inpatient rate (cases per 1,000 population)	11.60	17.71	6.12***
Inpatient primary care facilities	2.34	5.90	3.56***
Inpatient hospitals	9.30	21.11	11.82***
Inpatient public healthcare facilities	12.14	17.93	5.79***
Inpatient private healthcare facilities	6.59	9.19	2.60***
District x Year	1,480	1,506	

Note: Authors' calculation based on Susenas 2011–2016 data

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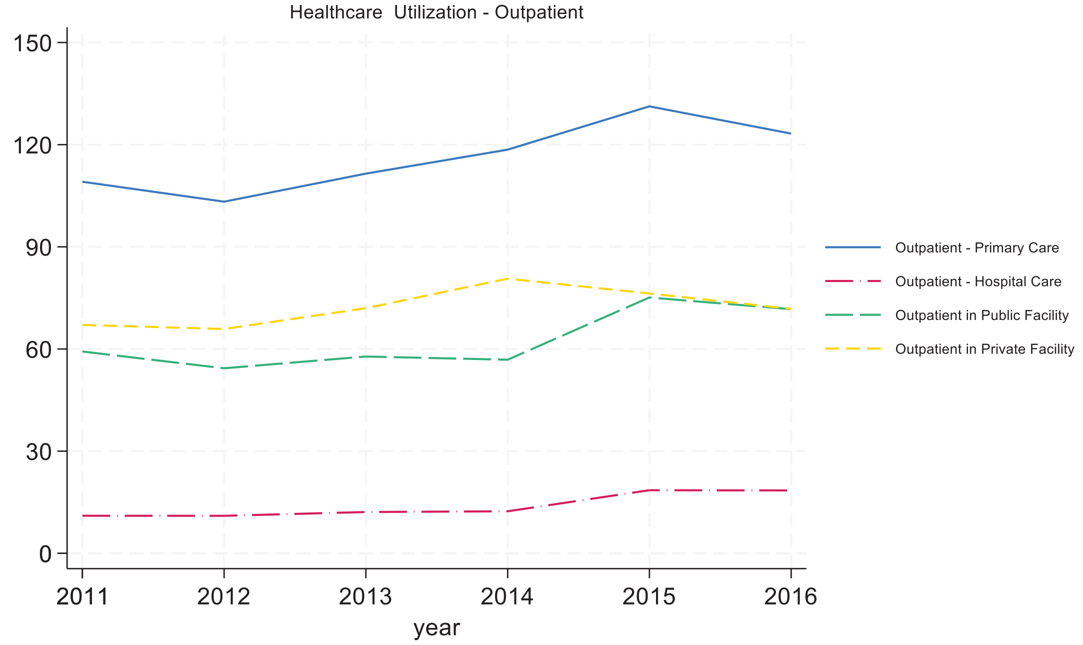
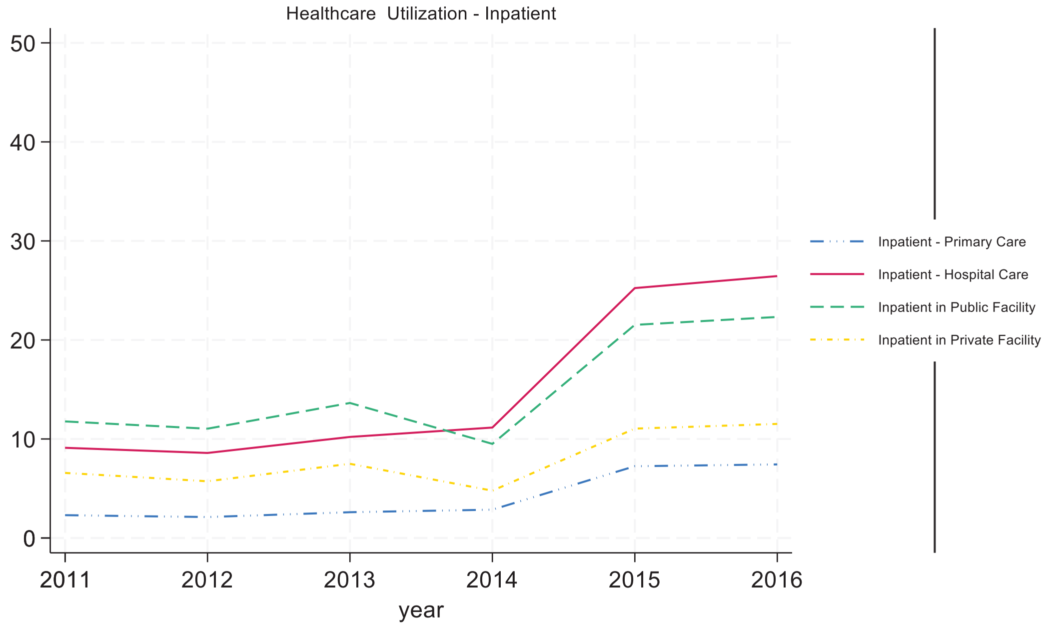
Figure 3A. Outpatient Care Utilization Trends (2011–2016)



Note: Y axis refers to utilization per 1,000 individuals

Figure 3B. Inpatient Care Utilization Trends (2011–2016)



Note: Y axis refers to utilization per 1,000 individuals

Estimation results

Tables 3 and 4 present the differences in utilization among all types of health insurance holders for outpatient and inpatient care in any type of providers (primary care facilities and hospitals) and ownership (public and private). Prior to the JKN program there was a positive association between the district health insurance coverage share and the rate of outpatient visits to primary care facilities, indicating an additional 0.156 visits per 1,000 population compared to the uninsured share (Table 3). On the contrary, inpatient visits to primary care facilities were negatively associated with the share of health insurance holders in the pre-JKN period. A possible explanation for this finding may be that inpatient visits to primary care facilities were mostly related to emergency care and baby deliveries. These findings may indicate that people with insurance prefer going to the hospital for labour and emergency care because hospitals provide better equipment, and this poses fewer risks for them. However, we found no correlation between the use of hospital services (outpatient and inpatient) and the health insurance share in the pre-JKN period.

When we interact coverage with post-JKN year dummies, the estimates indicate a strengthened positive association between health insurance coverage and hospital use (outpatient and inpatient). The association of outpatient and inpatient visits to hospital and insurance coverage strengthened by 0.037 and 0.056, respectively (Table 3). These findings from the post-JKN analysis indicate a significant change from the pre-JKN to post-JKN periods. The number of hospitals and other healthcare facilities joining JKN rose in the post-JKN period. JKN also provides a more comprehensive benefit package that did not exist in the previous healthcare insurance schemes at low premium rates (below actuarial costs) (CNN Indonesia, 2018). The availability of better benefits can further increase JKN enrolment and strengthen its association with the use of hospital care compared to the pre-JKN period.

Additionally, we do not observe an increased association in primary care usage (outpatient and inpatient) post-JKN. This may suggest that, in contrast to expectations, a rise in insurance enrolment did not increase utilization of primary care services but may indicate a rising preference for hospital care use. This seems to be particularly the case among new enrolees, primarily from SEHI and HIFP schemes (Figure 2). This is in contrast to our hypothesis that the referral system would promote greater use of outpatient primary care. It may indicate that the referral system did not work as expected. Another possible explanation might be that the Susenas survey only recorded the visit with treatment and not the primary care visits that were done only to obtain a referral. Given that most puskesmas are not equipped to handle basic cases (Bappenas/Kementerian PPN, 2019), individuals may seek referrals to go directly to hospitals for outpatient care. Moreover, JKN holder might prefer treated by specialist in hospitals rather than seeing a general practitioner (GP) at puskesmas.

Table 4 shows that during the pre-JKN period, the enrolment of health insurance was positively associated with healthcare use in outpatient care (public and private facilities by 0.102 and 0.100, respectively) and inpatient care (private facilities by 0.034). Only inpatients in public facilities were negatively associated with insurance coverage (-0.019). The positive association in private facilities was weakened after JKN, shown by the negative coefficient of private outpatient (-0.063) and private inpatient (-0.028) care use. However, the sum of pre- and post-JKN coefficients was positive. This finding indicates that the new enrolees after JKN are more inclined to use public facilities compared to private facilities.

Furthermore, the coefficients of the year dummies in Tables 3 and 4 confirm the patterns observed in Figures 3A and 3B, indicating that all types of healthcare utilization increased during the year dummies following the implementation of the JKN program (2015 and 2016) compared to the baseline year (2011). These dummy variables were designed to capture the changes unrelated to the variations in health insurance enrolment. Considering that Susenas data was recorded in March, it might be reasonable not to expect this observation as early as 2014. Additionally, we found that the coefficients for the post-JKN year dummies were more substantial for the use of outpatient care in primary care facilities, inpatient care in hospitals, and outpatient care in public healthcare facilities.

Tables 5 and 6 present the results of the JKN health insurance separated into three different schemes. Before the introduction of JKN, districts with a higher share of HIFP showed a positive correlation with the use of outpatient care in primary care facilities (0.177) and hospitals (0.020), as well as inpatient care in hospitals (0.022) (Table 5). However, the coefficient for inpatient care in primary care facilities was negative (0.016); this may be related to this scheme holder preferring to go to the hospital for labour and emergency care. Moreover, the positive coefficients of the interaction terms between the share of HIFP and the post-JKN period with hospital outpatient and inpatient visits were positive (0.025 and 0.019, respectively) (Table 5). This suggests that for this group the positive association between use and coverage is substantially strengthened as it doubled. For primary care outpatient visits (-0.117), the association was weakened but remained positive if added to the pre-JKN coefficient. This might imply that new HIFP scheme holders prefer to go directly to the hospital after JKN implementation for outpatient services. JKN seems to have enhanced the use of public healthcare facilities more than private healthcare facilities for the HIFP scheme (Table 6). These findings are in line with our prior expectations.

Next, MHI scheme holders are expected to use more healthcare services because they work in the formal sector, are in the middle class, and are better educated. We found that in the pre-JKN period, the district share of the MHI scheme was associated with a significantly lower rate of hospital inpatient visit (-0.184) and a higher rate of primary care inpatient visits (0.041). Outpatient visits (both in primary care facilities and hospitals) show non-significant correlations. The non-significant associations between MHI and healthcare use were unexpected, which may stem from the low variation in the change of the MHI share at district level over the years. Since we used fixed effects at district level, the between-district variation was absorbed. Since MHI have been covered for a long time, they have small unmet healthcare needs to be filled by BPJS Kesehatan. Therefore, they show fewer visits compared to other schemes. GoI also imposed a moratorium on civil servant recruitment starting from 2012 to 2013 (Kontan, 2012). With regard to these two reasons, we found small and non-significant associations with healthcare use.

These associations changed post JKN. The primary care outpatient visit association rose by 0.415 from the negative one in the pre-JKN period (-0.014) to a positive one (0.411). Similarly, the hospital outpatient (0.111) and inpatient (0.259) visit associations with MHI share rose post-JKN. Mandatory health insurance showed mixed findings pre-JKN and post-JKN, especially for use of inpatient services in public providers, as shown in Table 6. The sign was negative but not significant during the pre-JKN period (-0.0383). By contrast, it was positive and significant with post-JKN interaction (0.373). During the pre-JKN period, use of private inpatient care also showed a negative correlation (-0.045) but did not change post-JKN.

In all insurance analysis with public-private facilities, the findings differed from our hypothesis where private care use would increase after JKN implementation. This unexpected result also occurred when we divided it into different schemes for HIFP and MHI. Before the implementation of JKN, HIFP and MHI holders primarily had to go to public healthcare facilities as regulated by ASKES and Jamkesmas. Jamkesmas holders were limited to accessing public healthcare facilities, while ASKES holders could seek private secondary care after receiving a referral from a public primary care facility. After the implementation of JKN, they can go to public or private healthcare facilities as long as these facilities have a contract with BPJS Kesehatan. Many private healthcare facilities saw JKN as an opportunity. The data shows that around 2,147 (an 80% rise) new primary clinics and 798 (a 20% rise) new general practitioners joined JKN in the same period of 2014–2016 (Appendix Table A3) (Agustina, et al., 2019).

One possible explanation for the higher utilization of public facilities is the issue of availability. Public hospitals are accessible in every district (Trisnantoro & Listyani, 2018), whereas private hospitals collaborating with JKN may not be easily available there. Most private and newly developed hospitals are concentrated in urban areas of Java and Bali (Trisnantoro, 2019). Additionally, private hospitals cooperating with BPJS Kesehatan may not be willing to invest heavily in better equipped facilities (Health Policy Plus & TNP2K, 2018a). This might be because the private hospitals may perceive the currently used reimbursement rate from BPJS Kesehatan as insufficient to cover their costs (Health Policy Plus & TNP2K, 2018a). Consequently, with the growing enrolment in JKN schemes, readily available public hospitals are overflowed with patients. This indicates that public facilities continue to play a major role in healthcare provision.

Finally, the new SEHI scheme, only installed after the implementation of JKN, showed a clear positive association with hospital outpatient care use (0.198) and hospital inpatient care use (0.249) (Table 5). These correlation coefficients were larger compared to the other schemes, as we expected. This suggests that an increase in the number of people in a district covered with the SEHI associated scheme increases especially for hospital care use. However, they did not show any significant associations with the use of outpatient care in primary care facilities. Therefore, SEHI holders used their coverage for hospital care but not for primary care facilities. One possible explanation is that as they paid the premium out-of-pocket, they wanted to maximize their benefit and went directly to secondary care. This relatively high demand for inpatient care among self-enroled individuals potentially signals adverse selection: individuals may be opting for secondary care directly on their way to a hospital for treatment. It also suggests that the gatekeeping mechanism did not function as intended in the SEHI scheme, as the coefficients for primary care visits were never significant.

Table 3. Healthcare Utilization and Possession of any Type of Health Insurance Scheme (Types of Providers: Primary Care Facilities vs Hospitals)

	Outpatient		Inpatient	
	(1) Primary Care Facilities	(2) Hospitals	(3) Primary Care Facilities	(4) Hospitals
Have any type of insurance	0.156***	0.0184	-0.0105*	-0.00240
	(0.0525)	(0.0114)	(0.00590)	(0.0112)
Have any type of insurance*POST	-0.0728	0.0371***	-0.00641	0.0566***
	(0.0495)	(0.0107)	(0.00556)	(0.0106)
Dummy Year				
2012	-5.683***	0.0103	-0.198	-0.450
	(1.533)	(0.333)	(0.172)	(0.328)
2013	0.375	1.008***	0.415**	1.279***
	(1.661)	(0.361)	(0.187)	(0.356)
2014	11.18***	-0.835	1.113***	-0.993
	(3.008)	(0.654)	(0.338)	(0.644)
2015	25.16***	5.707***	5.469***	13.47***
	(2.881)	(0.626)	(0.324)	(0.617)
2016	17.79***	5.548***	5.679***	14.59***
	(2.950)	(0.641)	(0.332)	(0.632)
Constant	102.3***	9.998***	2.765***	9.089***
	(2.560)	(0.556)	(0.288)	(0.548)
District Fixed Effect	Yes	Yes	Yes	Yes
N	2,868	2,868	2,868	2,868

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Both primary care facilities and hospitals include utilization in public or private healthcare providers.

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Table 4. Healthcare Utilization and Possession of any Type of Health Insurance Scheme (Ownership: Public vs Private)

	Outpatient		Inpatient	
	(1) Public	(2) Private	(3) Public	(4) Private
Have any type of insurance	0.102***	0.100***	-0.0199*	0.0337***
	(0.0360)	(0.0382)	(0.0107)	(0.00806)
Have any type of insurance*POST	0.0173	-0.0626*	0.0427***	-0.0283***
	(0.0339)	(0.0360)	(0.0101)	(0.00759)
Dummy Year				
2012	-4.718***	-1.199	-0.616**	-0.825***
	(1.051)	(1.116)	(0.313)	(0.235)
2013	-2.760**	3.656***	2.256***	0.630**
	(1.138)	(1.209)	(0.339)	(0.255)
2014	-4.290**	15.21***	-4.170***	-0.606
	(2.062)	(2.189)	(0.614)	(0.462)
2015	14.12***	12.42***	7.809***	5.947***
	(1.975)	(2.097)	(0.589)	(0.442)
2016	10.86***	8.213***	8.397***	6.568***
	(2.022)	(2.147)	(0.603)	(0.453)
Constant	54.03***	63.34***	12.51***	5.034***
	(1.755)	(1.863)	(0.523)	(0.393)
District Fixed Effect	Yes	Yes	Yes	Yes
N	2,868	2,868	2,868	2,868

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Both public and private healthcare providers include utilization in primary healthcare facilities or hospitals.

Table 5. Healthcare Utilization and Health Insurance Coverage with Post-JKN Interaction (Types of Providers: Primary Care Facilities vs Hospitals)

	Outpatient		Inpatient	
	(1) Primary Care Facilities	(2) Hospitals	(3) Primary Care Facilities	(4) Hospitals
Health Insurance for the Poor	0.177***	0.0201*	-0.0158**	0.0216*
	(0.0548)	(0.0118)	(0.00615)	(0.0113)
Mandatory Health Insurance	-0.0144	0.00721	0.0405***	-0.184***
	(0.137)	(0.0294)	(0.0153)	(0.0281)
Interaction of share and post-JKN (1 if 2014 onwards)				
Self-enroled Health Insurance	-0.201	0.198***	-0.0462***	0.249***
	(0.128)	(0.0276)	(0.0144)	(0.0263)
Health Insurance for the Poor*POST	-0.117**	0.0248**	-0.000235	0.0195*
	(0.0527)	(0.0114)	(0.00592)	(0.0108)
Mandatory Health Insurance*POST	0.415***	0.111***	-0.0361**	0.259***
	(0.155)	(0.0335)	(0.0174)	(0.0319)
Dummy Year				
2012	-5.563***	-0.0107	0.000613	-1.216***
	(1.628)	(0.351)	(0.183)	(0.335)
2013	-0.0140	0.958**	0.740***	0.0203
	(1.804)	(0.389)	(0.203)	(0.371)
2014	6.897**	-1.252*	1.467***	-2.913***
	(3.363)	(0.725)	(0.378)	(0.691)
2015	24.82***	4.029***	6.228***	9.529***
	(3.238)	(0.698)	(0.364)	(0.665)
2016	20.37***	2.767***	6.728***	9.022***
	(3.659)	(0.789)	(0.411)	(0.752)
Constant	103.8***	10.02***	2.120***	11.27***
	(3.106)	(0.670)	(0.349)	(0.638)
N	2,837	2,837	2,837	2,837

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Both primary care facilities and hospitals include utilization in public or private healthcare providers.

2

Table 6. Healthcare Utilization and Health Insurance Coverage with Post-JKN Interaction (Ownership: Public vs Private)

	Outpatient		Inpatient	
	(1) Public	(2) Private	(3) Public	(4) Private
Health Insurance for the Poor	0.122***	0.105***	-0.0211*	0.0419***
	(0.0375)	(0.0399)	(0.0112)	(0.00825)
Mandatory Health Insurance	-0.0383	0.0272	0.0188	-0.0451**
	(0.0935)	(0.0995)	(0.0279)	(0.0206)
Interaction of share and post-JKN (1 if 2014 onwards)				
Self-enroled Health Insurance	-0.114	0.111	0.0575**	0.121***
	(0.0878)	(0.0934)	(0.0262)	(0.0193)
Health Insurance for the Poor*POST	-0.0157	-0.0907**	0.0496***	-0.0409***
	(0.0361)	(0.0384)	(0.0108)	(0.00794)
Mandatory Health Insurance*POST	0.373***	0.185	-0.0498	0.0167
	(0.106)	(0.113)	(0.0317)	(0.0234)
Dummy Year				
2012	-4.714***	-1.144	-0.524	-0.999***
	(1.115)	(1.186)	(0.332)	(0.245)
2013	-3.223***	3.572***	2.430***	0.273
	(1.236)	(1.314)	(0.368)	(0.272)
2014	-7.516***	13.35***	-3.204***	-0.885*
	(2.303)	(2.450)	(0.686)	(0.507)
2015	13.99***	10.32***	8.271***	4.328***
	(2.218)	(2.359)	(0.661)	(0.488)
2016	13.07***	5.755**	8.482***	3.901***
	(2.506)	(2.666)	(0.747)	(0.551)
Constant	55.18***	64.04***	11.95***	5.865***
	(2.127)	(2.262)	(0.634)	(0.468)
N	2,837	2,837	2,837	2,837

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Both public and private healthcare providers include utilization in primary healthcare facilities or hospitals.

2.6. Conclusion

While our results can and should not be interpreted as estimates of the causal impact of different types of insurance, they may provide valuable insights into the changing patterns of association following the introduction of JKN. There are some conclusions to be drawn from this research. First, JKN has successfully increased health insurance coverage in Indonesia. Our findings indicate that the coverage rise was also associated with higher healthcare utilization in the post-JKN period. We observed significant increases in hospital outpatient and inpatient care compared to the pre-JKN period. Second, and perhaps surprisingly, the positive pre-JKN association of health insurance coverage for outpatient care in primary care was not significantly strengthened after JKN implementation. This may indicate that the gatekeeping mechanism did not work properly.

Third, taking the health insurance schemes into consideration, we found that the HIFP share in a district was associated with the overall healthcare use, except for private care facilities, as we expected. This may suggest that the insured poor were not frequent visitors to private care facilities and this has not changed post JKN. Fourth, the overall pattern that we observed was that individuals covered by JKN preferred using public healthcare facilities to using private ones. Similarly, we also found that the MHI scheme did not show a significant positive association for visits to private healthcare facilities post-JKN. In contrast to the other schemes, we found a significant positive association of private hospital inpatient visits with SEHI coverage at district level. The rising utilization of public healthcare needs attention as Indonesia seeks to address inequalities in healthcare access. The government's intervention in healthcare provision alone cannot fulfill all healthcare needs in the country.

Lastly, as we expected, the SEHI scheme showed the strongest positive association with healthcare utilization in hospitals. This suggests that a substantial degree of adverse selection is likely to account for the rise of the self-enrolled or non-poor informal scheme in JKN. Evidence from BPJS Kesehatan demonstrates that this scheme has a substantial usage claim ratio but does not consistently pay the premiums. As a result, the government is indirectly 'subsidizing' this scheme to ensure the continued operation of JKN. This may pose a potential threat to the financial sustainability of the JKN system in the long term.

3

CHAPTER 3

Does geographic spending variation exacerbate healthcare benefit inequality? A benefit incidence analysis for Indonesia

With Eddy Van Doorslaer, Menno Pradhan and Robert Sparrow

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Abstract

The Indonesian government has made ambitious steps to achieve Universal Health Coverage through the newly formed National Health Insurance (*Jaminan Kesehatan Nasional* – JKN), establishing a single-payer insurance agency and prospective provider payment mechanism. This study aims to assess the benefit incidence of healthcare funding in the JKN era, and its distribution by socioeconomic status considering regional variation in unit costs. We evaluate whether the benefit incidence of funding is skewed towards urban and wealthier households. We also investigate whether standard benefit incidence analysis using national unit costs underestimates regional disparities in healthcare funding. Lastly, we examine whether the design of the JKN provider payment system exacerbates regional inequalities in healthcare treatment intensity and value of treatment. The analysis relies on Indonesia's annual National Socio-economic Survey (SUSENAS) and administrative data on JKN provider payments from 2015 to 2017, combined at district level for 466 districts. We find that the benefit incidence of healthcare expenditure favours the wealthier groups. We also observe substantial variation in hospital unit costs across regions in Indonesia. As a result, standard benefit incidence analysis (using national average unit transfers) underestimates the inequality due to regional disparities in healthcare supply and value of treatment. The JKN provider payment seems to favour relatively wealthier regions that harbour more advanced healthcare services. Urban dwellers and people living in Java and Bali also enjoy greater healthcare benefit incidence compared to rural areas and the other islands.

3.1 Introduction

Indonesia introduced the National Health Insurance System (Jaminan Kesehatan Nasional – JKN) in 2014 to achieve universal health coverage by 2024. Mandated by Indonesian Law Number 40 in 2004 regarding the National Social Security System, the JKN consolidated existing mandatory social health insurance schemes (public servants, military, police and the formal private sector) and the subsidized insurance to the poor. In addition, informal sector workers, accounting for around 60% of the Indonesian labour force, were required to self-enrol. JKN is arguably one of the largest single-payer health insurance systems in the world (The Lancet, 2019). By October 2020, JKN had enrolled around 223,5 million members, representing approximately 82% of the Indonesian population (DJSN, 2020). JKN covers care from both public and private providers, including 22,971 out of 27,694 primary care providers (83%), 2,487 out of 2,925 hospitals (85%), as well as groups of pharmacists and medical laboratories (DJSN, 2020; BPJS Kesehatan, 2018; Ministry of Health, 2020).

One of the main criticisms of the JKN design concerns its provider payment system that would be favouring municipalities and the better-off regions (Trisnantoro, 2019). With the introduction of prospective payments for secondary care, the compensation to healthcare providers increases with delivering more advance services, which are usually more abundant in urban hospitals and clinics. Primary healthcare payments under JKN are capitation based, determined by the number of enrolled members registered in the service catchment area, the available providers and the treatment intensity of service provision. As a result, better-equipped service providers are more likely to receive relatively larger provider payments, which may exacerbate regional disparities in healthcare treatment intensity and value.

Previous studies of the benefit incidence of healthcare spending in Indonesia have relied on socio-economic variation in healthcare utilization combined with constant national unit costs of healthcare (Lanjouw et al., 2002; O'Donnell et al., 2007). An important limitation of constant unit costs is that it assumes that the same type of healthcare service offers the same treatment intensity and value across the country. Utilization rates and national unit costs do not capture geographic disparities in healthcare service and intensity of treatment. For example, utilization of healthcare at an advanced hospital in the capital Jakarta will most likely be more intensive and involve more resources than the same type of service provided at a lower level hospital in a remote district, and thereby reflect a larger monetary value in offering the same public service. In this case, a benefit incidence analysis based on constant national unit costs will underestimate regional and socio-economic inequalities in who benefits from of healthcare spending in Indonesia.

Therefore, our study conducts a Benefit Incidence Analysis (BIA) of healthcare financing in Indonesia, using Indonesia's JKN funding of healthcare providers to account for regional disparities in healthcare supply and intensity of treatment. We have three main objectives. First, we assess the benefit incidence of healthcare spending by region and socio-economic status, and evaluate whether this spending is skewed towards urban and wealthier households. Second, we investigate whether standard BIA using constant national unit costs underestimates regional disparities in JKN funding to healthcare providers. Third, we examine whether the design of the JKN provider payment system exacerbates regional inequalities in healthcare supply and treatment intensity.

This paper contributes to the BIA literature by using healthcare provider claims and capitation data of JKN, which provides accurate and detailed regional variation in unit costs for different types of healthcare services. The data is used to calculate unit costs at district level, reflecting the monetary value of health service offered in those districts as well as the regional variation in treatment intensity and supply of healthcare. By comparing these results to a standard BIA approach (with constant national unit costs), we can quantify the bias in the benefit incidence. A small number of studies use administrative data to capture regional differences in healthcare spending, for example in the case of Australia (Ellis et al., 2013) and Hungary (Bíró and Prinzba, 2020). Moreover, few studies distinguish regional variation in spending for hospital and primary care in low- and middle-income countries. For example, Anselmi et al. (2015) study differences in regional spending in Mozambique but limit their scope to outpatient care at primary and secondary facilities.

We also contribute to further understanding of the distributional implications of Indonesia's JKN. Johar et al. (2018) use the National Socio-Economic Surveys from 2011-2016 to show that equity in access to healthcare improved after the introduction of JKN. Based on household panel data from the Indonesian Family Live Survey (IFLS) from 1993-2014/15, Mulyanto, Kringos and Kunst (2019) find similar patterns for inpatient utilization but not for outpatient care in the first year of the JKN. Also using the IFLS data, for 2007 and 2014/15, Erlangga, Ali and Bloor (2019) show that JKN increased utilization of outpatient and inpatient care, but they question whether this reduces inequities in access, as the effects were larger for the self-enrolled group than for the subsidized poor. Health Policy Plus and TNP2K (2018) analyse JKN hospital expenditure and find that expenditure shares for the islands of Java, Bali and Sulawesi are disproportionately large relative to their population size, as is the expenditure share enjoyed by the rich. Our BIA analysis adds to these studies, as we assess JKN spending on both primary and secondary care, accounting for almost all of JKN disbursements. In addition, while inequity in access may have been declining over time, we demonstrate that ignoring regional variation in treatment intensity of care and the allocation rule underlying the provider payment system will underestimate the disparities in benefit incidence.

We assess the health benefit incidence by combining the national socio-economic survey (Susenas) and administrative data from the Health Insurance Agency (BPJS-Kesehatan). These two data sources cover a three-year period from 2015-2017. The Susenas data provides information on per capita expenditure and healthcare utilization for various types of healthcare. In addition, BPJS-Kesehatan administrative data on provider payments allow us to construct district specific unit costs for these health services, aggregated into primary outpatient care, and secondary inpatient and outpatient care.

We find that the benefit incidence of healthcare funding is skewed towards the wealthier groups, and that using constant national unit costs underestimates the inequality in benefit incidence of healthcare spending for all types of care. However, we find no changes in the overall benefit incidence distribution during the first three years of the JKN, suggesting that its provider payment mechanism maintains geographic and socioeconomic disparities but does not exacerbate these over time. Urban dwellers and people living on Java and Bali also enjoy a greater healthcare benefit compared to rural areas and the other islands.

The next section elaborates on the JKN financing system. Section 3.3 sets out the BIA methods and section 3.4 describes the data. In section 3.5 we present and discusses the results and section 3.6 concludes.

3.2 JKN and healthcare financing in Indonesia

3.2.1 Provider Payment in the JKN Era

A defining feature of the JKN reforms in Indonesia is the implementation of a single-payer healthcare system, by establishing the Social Security Agency in Health (Badan Penyelenggara Jaminan Sosial-Kesehatan – BPJS Kesehatan). As a single-payer for health insurance in Indonesia, BPJS-Kesehatan is responsible for the provider payments and collecting the premium contributions. The Indonesian government, through the Ministry of Health, sets the service standards and rules for the referral process. JKN members are not limited in seeking primary health care but need to obtain a referral to access higher level care. Primary care facilities (public and private) have a role as gate-keeper to regulate the flow to secondary hospital and tertiary specialized care.

Payment systems for secondary care are claims-based and regulated through Case-Based Groups (CBGs) of diagnosed-related groups called InaCBGs (Indonesian CBGs), which are calculated based on grouping diagnoses and procedures with similar clinical characteristics, resources and treatment costs. InaCBG tariffs are determined by the class of hospital (class A, B, C, or D), leading to relatively larger claims for more advanced hospitals. To encourage the involvement of private sector providers in JKN, InaCBG tariffs were increased by 3% for private inpatient and by 5% for private outpatient care (Agustina et al. 2019). The InaCBG tariffs also accommodate price differences across regions.[1]

Primary care providers registered with BPJS-Kesehatan receive JKN funding predominantly through a capitation scheme for outpatient service. In the capitation scheme, primary care providers receive a monthly upfront payment per JKN participant registered at the facility, irrespective of the actual services delivered. Capitation payments are meant to encourage independence and flexibility of primary care providers in managing their finances. Community health centres that meet the full requirements of BPJS-Kesehatan receive 6,000 IDR (around 0.46 USD) per member per month.2 This capitation amount is reduced when these facilities fall short of the requirements. Private providers receive larger capitation amounts, ranging from 8,000 (0.57 USD) to 10,000 IDR (0.71 USD), depending on their medical staff and service availability. Some services are not covered by capitation payments but are funded on a fee-for-service basis (referred to as non-capitation cases), such as antenatal care, deliveries and family planning services.

[1] Based on the consumer price index, districts are classified into 5 groups. For each group a price correction factor is applied. The InaCBG tariffs therefore accommodate price differences between the 5 groups but ignore the variation within the groups or within districts.
[2] One USD equals about 14,000 IDR (February 2020).

3.2.2. JKN Sources of payment

The JKN funding is pooled and distributed centrally by BPJS-Kesehatan. The funding comes from various sources. First, funding from the national government, coordinated by the Ministry of Finance and Ministry of Health, is earmarked for the subsidised insurance targeted to the indigent (37% of the JKN budget in 2016), and the premiums for civil servants, state-owned enterprise employees, and military and police (23%). Second, some provincial and district governments provide funding to cover premiums for informal sector workers that are required to self-enrol (5%). Third, voluntary registered informal sector workers contribute monthly premiums out-of-pocket (9%). Finally, the private formal sector has the responsibility to register their employees and share in the contribution of their JKN premiums (26%). Table 1 summarizes the shares of each source of contributions to the JKN.

In absolute amounts, total JKN financing almost doubled from 3.23 billion USD in 2014 to 6.26 billion USD in 2017. Hospital inpatient claims accounted for 3.67 billion USD or around 58.6% of total JKN funds disbursed in 2017, while 1.66 billion USD (or 26.4%) was allocated to hospital outpatient care. Combined, payments for hospital curative services amounted to 85% of the total JKN budget. Primary care services take a share of around 14% of the budget, even though outpatient primary care utilization accounts for around two-thirds of all JKN patient contacts.

Table 1. Distribution of JKN source of payment (%)

Type of membership	2014	2015	2016
Subsidised poor and indigent (national government budget) (A)	49.0	37.7	36.8
Civil servants, state-owned enterprise, military and police (national government budget) (C)	34.4	28.5	22.8
Self-enrolled subsidised by districts and provinces (local government budgets) (B)	3.3	4.5	5.4
Self-enrolled voluntary (individual premiums) (D)	4.6	8.9	8.5
Private sector (individual premiums) (E)	8.7	20.5	26.4
Total government share (A+B+C)	86.7	70.7	65
Total private share (D+E)	13.3	29.4	34.9

Source: (Ahsan, 2017)

3.2.3. Benefit Coverage

The JKN program covers a basic healthcare benefit package, including outpatient and inpatient care (starting from the appointed primary care, and up to secondary and tertiary care based on referral), maternal and child healthcare, dental health services (basic and advanced), advanced health services such as cancer therapies and haemodialysis, as well as health-related equipment with limited upper value or quantity, such as eyeglasses and hearing aids. Some healthcare is excluded, such as cosmetic treatment. Patients with JKN coverage are exempt from co-payments for medicine and medical items as long as the appropriate referral stages have been followed (Agustina et al., 2019). In principle, co-payments are not allowed under JKN. In practice, out-of-pocket payments are still widely observed. This could be due to, for example, ex-post upgrading of ward class, purchasing over-the-counter medicine outside treatment facilities and products that are not based on prescriptions, or traditional medicine.

The medical services provided under JKN are the same for all patients, but the class of ward may differ. Non-contributory subsidised JKN members are entitled to basic third-class hospital rooms for inpatient service. A self-enrolled or formal private sector JKN member may choose a class of hospital room (first, second and third class) that corresponds with their monthly minimum premium. It is also possible to take up private health insurance as a supplementary to JKN in order to cover extra benefits such as upgrades for hospital rooms, while upgrades can also be purchased out-of-pocket.

3.3. Methods

Benefit Incidence Analysis (BIA) aims to evaluate the distribution of a public subsidy by socio-economic status within a population (e.g. Demery, 2000; O'Donnell et al., 2008; McIntyre and Ataguba, 2011). We interpreted utilization of healthcare services as a transfer (or benefit) of public health spending (or subsidy) to an individual. BIA then described at an aggregate level how different population groups benefit from overall public health spending; for example, to what extent the benefits go disproportionately to the poor (e.g. due to government targeting) or to the wealthy (e.g. due to better access to public services).

3.3.1. Average Benefit Incidence Analysis with constant unit costs

To formalize the total healthcare financing benefit, we need to aggregate the transferred subsidy of all types of health services. This total subsidy for healthcare supplied under JKN is channelled through healthcare providers in the form of hospital claims (T^{cl}) for inpatient and outpatient care, capitation funding (T^{cap}) for primary outpatient care, and non-capitation reimbursements ($T^{non-cap}$) for primary inpatient care:

$$T = T^{cl} + T^{cap} + T^{non-cap} \qquad (1)$$

To assess how this total subsidy was shared among socio-economic groups or regions, we need to consider who used healthcare. Using healthcare is valued at the unit cost of a healthcare service, $\frac{T_i}{Q_i}$, defined as the average provider payment for reimbursing healthcare facilities for a delivered service i (i.e. outpatient or inpatient care at primary or secondary providers). Typically, standard BIA relies on the assumption that this unit cost is constant across the population. The total subsidy S_{ij} that was transferred to socio-economic group j for service i is then calculated by multiplying total utilization of the group, Q_i, with the unit cost

$$S_{ij} = Q_{ij} \frac{T_i}{Q_i} \qquad (2)$$

Aggregating the subsidy for all services i received by group j yields the total benefit incidence. Finally, dividing the total transfer S_{ij} by total JKN healthcare spending T expresses the total benefit incidence in terms of the shares of the transfer received by group j :

$$s_j = \sum_i \frac{Q_{ij}}{Q_i} \left[\frac{T_i}{T}\right] \qquad (3)$$

3.3.2. Average Benefit Incidence Analysis with regional variation in unit costs

The availability of information on JKN spending by district allows us to test whether the provider payment system affects the distribution of benefit incidence of public health spending. With the claims and capitation data, we can relax the assumption of constant unit costs and allow for variation by district. As the JKN claims are based on InaCBGs, they offer a realistic reflection of the variation in supply and value of care offered in districts. We therefore assume that the district specific JKN unit costs are a good proxy for the regional variation in the implicit subsidy of healthcare utilization. The unit costs for service i in district k is then calculated by dividing the JKN transfer amount to the district k for that service i (T_i^k) by the number of units of care on which the JKN claims in district k (q_i^k) are based, as measured in BPJS-*Kesehatan* administrative records. The average subsidy amount per unit of care used in quintile j for service i in district k (S_{ij}^k) is obtained by multiplying this unit cost by the utilization of this group (Q_{ij}^k) as measured in the SUSENAS survey:

$$S_{ij}^k = Q_{ij}^k \frac{T_i^k}{q_i^k} \qquad (4)$$

The implicit assumption is that also non JKN use of care in the district receives the same subsidy as JKN funded care. We can define spending in equation (4) for four different categories of services: hospital inpatient (HI), hospital outpatient (HO), primary outpatient (PO) and primary inpatient care.3 The relevant data on JKN spending came from the hospital claims for inpatient services (T^k_{HI}) and hospital outpatient services (T^k_{HO}), and the primary care capitation payments (T^k_{cap}) to districts. We excluded primary care non-capitation claims from our calculations because this amount is relatively small, at around 1% of JKN spending (Pusat Pembiayaan dan Jaminan Kesehatan Kementerian Kesehatan, 2017). Total healthcare spending T thus reflects the summation of national hospital claims and capitation payments. The overall healthcare benefit for group j can then be expressed as

$$S_j = \sum_k Q^k_{HIj} \frac{T^k_{HI}}{q^k_{HI}} + Q^k_{HOj} \frac{T^k_{HO}}{q^k_{HO}} + Q^k_{POj} \frac{T^k_{cap}}{q^k_{PO}} \quad (5)$$

The proportion of the benefit transferred to socio-economic group j is then written as

$$s_j = S_j / \sum_j S_j \quad (6)$$

3.3.3. Concentration Curve and Concentration Index

We use concentration curves (CC) to illustrate the relative inequality of healthcare benefit. Concentration curves describe the benefit incidence of healthcare by plotting the cumulative proportion of healthcare use against the cumulative proportion of the population ranked by per capita household expenditure per adult equivalent (O'Donnell et al., 2008). If the healthcare funds are distributed pro-poor then the CC should lie above the 45 degree equity line, whereas it would fall below the equity line in case of a pro-rich distribution.

The inequality implied by the CC can be expressed in terms of a Concentration Index (CI), which reflects twice the area between the CC and the diagonal (Wagstaff & van Doorslaer, 2000). The concentration index (CI) can be calculated as

$$C = \frac{1}{n} \sum_{i=1}^{n} \frac{h_i}{\bar{h}} (2R_i - 1) \quad (6)$$

where n is the sample size, h_i is an individual's healthcare benefit in monetary terms with mean $\bar{h}$, and R_i is the fractional rank of individual i in the distribution of per capita expenditure (with

[3] About 36% of total community health centres in Indonesia provide inpatient services, although the number of beds per facility is limited.

i = 1 for the poorest and $i = n$ for the richest). The value of the CI is negative for a pro-poor distribution of the JKN funding and positive for a pro-rich distribution, while an equal distribution yields a CI of zero. Dominance of distributions can be verified (and tested) by checking whether a CC lies everywhere above another CC or above the Lorenz curve measuring household income/expenditure inequality (O'Donnell *et al.*, 2008)

3.4. Data

We combined the National Socio-economic Household Survey (Susenas) for 2015, 2016 and 2017 with administrative data from BPJS-*Kesehatan* over the same time period at district level. The Susenas data is representative at national and district level, and provides information on utilisation of primary and secondary healthcare services, and per capita expenditure. The sample size of Susenas is 1,097,719 individuals in 2015, 1,109,749 in 2016 and 1,132,749 in 2017. We used the Susenas sampling weights to ensure that the micro data is representative at the district and national level. BPJS-*Kesehatan* data provide JKN hospital claims data and capitation payments for 466 of Indonesia's 514 districts, and also records inpatient and outpatient contacts/consultations of JKN registered individuals per district.

To implement the BIA with our combined data we proceeded in several steps. First, we calculated the unit costs based on the BPJS-Kesehatan data. The unit costs of each health service and for each district are calculated by dividing the total sum of district JKN claims (from all JKN-registered hospitals) by the total outpatient consultations or inpatient contacts in a district. Unfortunately, the utilization of JKN members of outpatient primary care (q_{PO}^{k}) is not in the JKN administrative data as the payments are made on a capitation basis. We therefore estimated this using Susenas data by multiplying the total utilization for outpatient primary care services in district k by the fraction of the population in the district k that is a JKN member.

We can interpret the unit cost or unit transfer as the monetary value of a treatment and assume that it varies with the intensity of care provision in districts. As our analysis relies on JKN disbursements as a proxy for healthcare financing disparities across regions, we also assume that the variation in district mean JKN spending appropriately captures the actual variation in healthcare benefits obtained for all district inhabitants, including both JKN members and non-members.[4] This assumption is valid if unit costs are supply driven, and JKN and non-JKN members use similar services.

Second, we use the Susenas household survey data to calculate the distribution of healthcare utilization by socio-economic group per district (Q_{ij}^{k}). The household survey offers socio-economic characteristics of the district populations that the BPJS-Kesehatan does not include. We measure contact rates of each type of healthcare in Susenas, which records individual hospital or primary outpatient care in the month before the survey (around March for each year). We define primary care facilities as community health centres (Puskesmas) and their local subsidiaries, polyclinics and GP practices, while exclude traditional practices. The inpatient care recall period is the year preceding the survey. Because the district claims data is on an annual basis, we annualized outpatient use.

To evaluate the cost of health services distributed across rich and poor, we ranked individuals based on the national distribution of per capita expenditure and define quintiles (where quintile 1 is the poorest group and quintile 5 the wealthiest). Per capita expenditure as well as the unit costs were also adjusted for regional price differences using a provincial consumer price index (taking Jakarta province in 2014 as base year).

3.5. Results and Discussion

3.5.1. How do unit costs vary by district?

The procedure described in the previous section generates an estimate of the regional variation in the unit cost of different healthcare services across districts. We find a positive correlation between average per capita household expenditure and hospital unit costs (Figure 1). The relatively expensive care provided in Jakarta drives much of this association, with a unit cost of 26.50 USD per hospital outpatient contact (about 50% higher than the national average of 17.50 USD) and 530 USD per inpatient care contact (i.e. about 80% higher than the national

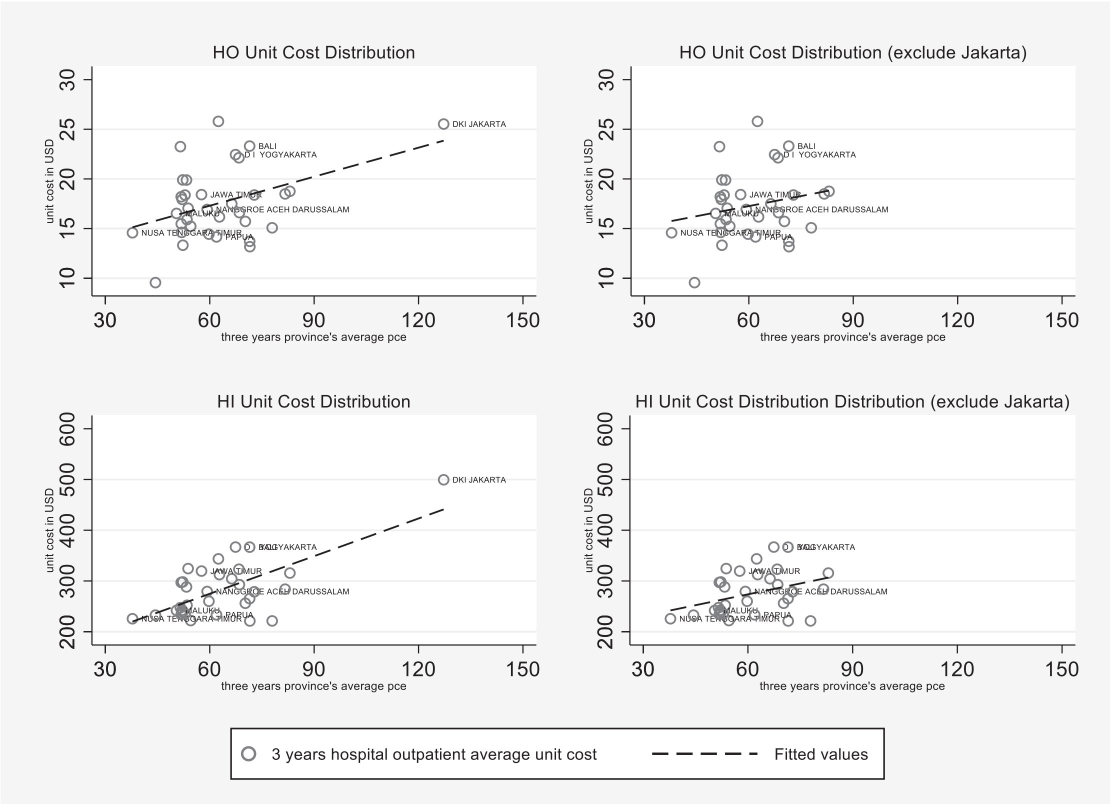
[4] By December 2017 around 73% of the total population was enrolled into JKN and almost 80% of all hospitals in Indonesia had joined JKN in 2016. For primary care, all community health centres joined JKN.

average of 291.80 USD). Nevertheless, a positive correlation remains visible when we exclude Jakarta from the scatterplot.

The variation in regional hospital unit costs in Figure 1 may be related to the availability of more advanced type hospitals (Hospital class A or B) or tertiary healthcare providers. A district or city with a class A (tertiary care) hospital will receive greater JKN disbursements than those without because they can offer a wider variety of treatment intensity and supply of medical care. These more advanced hospitals are not equally distributed across the country. (Trisnantoro, 2019) finds that two-thirds of the 61 class A hospitals in Indonesia are located in Java Island and 16 of these are in Jakarta. Our approach attributes unit costs to the place of (hospital) delivery, not the place of residence of the user. So if a resident of another district than Jakarta receives (tertiary) hospital care in Jakarta, the benefit is attributed to Jakarta residents, not the non-Jakarta residents receiving it.

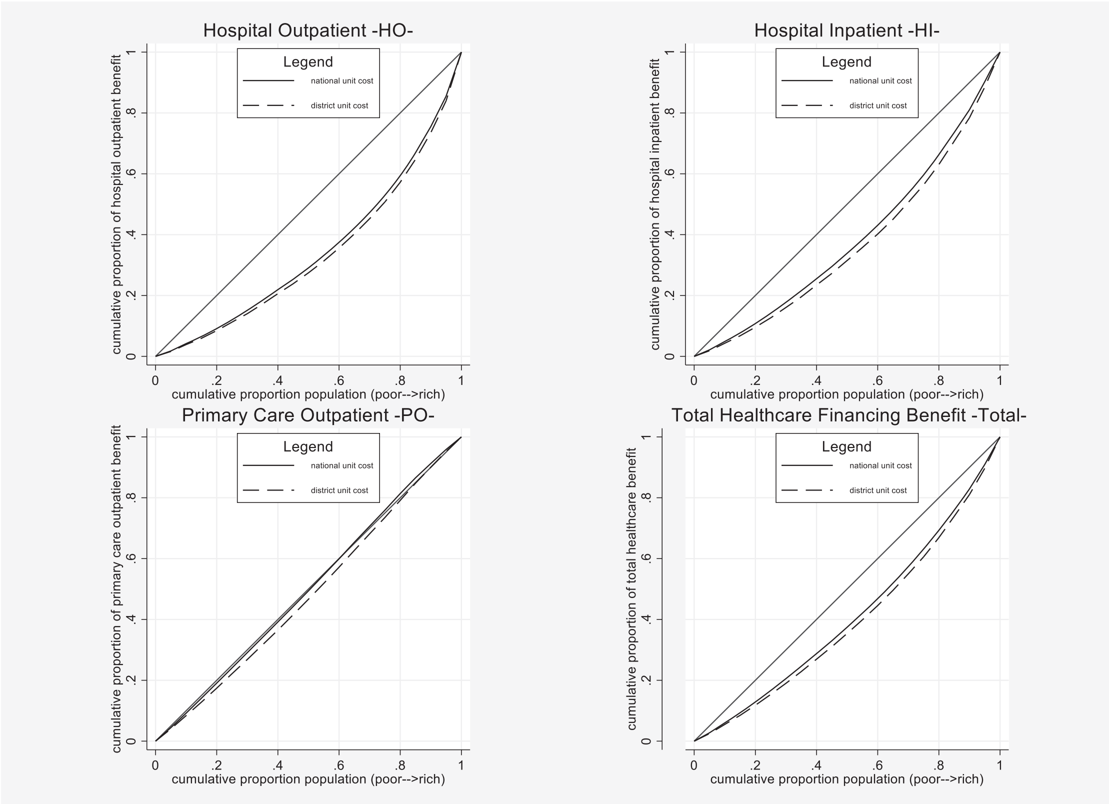
For primary care unit costs we use annual capitation payments at district level over the period 2015-2017 and Susenas primary outpatient service utilization. We find that district primary care unit costs do not vary much across districts, with the total capitation payments more proportional to the respective population sizes (see Figure A4 in the online Appendix).

Figure 1. Association between mean unit cost and mean household expenditure, by province, for outpatient and inpatient hospital care (Reviewer 1 Point 9)



Note: HO refers to hospital outpatient and HI to hospital inpatient care. The Y-axis shows three years averages of province specific unit costs derived from the BPJS-*Kesehatan* records on inpatient and outpatient claims and cases per district. The X-axis shows three years province averages of per capita expenditure derived from SUSENAS 2015-2017. The dash line represents a linear regression line. R-squared include Jakarta HO (0.1742) and HI (0.4559). R-squared exclude Jakarta HO (0.0456) and HI (0.1296).

Figure 2. Comparison of concentration curves with national unit cost and district-specific unit cost, for hospital (outpatient and inpatient) and primary care outpatient benefit (2017)



Note: HO: Hospital Outpatient; HI: Hospital Inpatient; PO: Primary Care Outpatient. The y-axis plots the cumulative density of a healthcare benefit incidence for individuals ranked by per capita expenditure in 2017.

3

3.5.2. Socioeconomic Distribution of Health Benefits after JKN

Table 2 provides an overview of the socioeconomic distribution of the utilization rate, standard benefit incidence shares, district-weighted unit costs and weighted benefit incidence shares for all three types of healthcare services. We divide the population into 5 quintiles based on per capita household expenditure in each year.

For the district-weighted hospital unit costs we find that the gap between the richest and poorest quintiles persists, although it does decline over time. Table 2 (column 3) shows that for the richest quintile the hospital inpatient unit costs in 2017 are 40 USD (17 percent) higher than for the poorest quintile. This difference declined to 26 USD (11 percent) in 2015. The unit costs for hospital outpatient care and primary care are smaller in nominal terms but show a similar gradient and trend (Table 2, column 7 and 11).

The utilization rates (per 100 individuals) for hospital inpatient, hospital outpatient and primary outpatient care in the past year are reported in columns 1, 5 and 9. Hospital utilization is highly skewed towards the wealthier groups. The hospital inpatient contact rate for the fifth quintile is almost three times that of the poorest quintile, and the hospital outpatient contact rate is more than four times larger. In contrast, outpatient contact rates at primary providers show a nearly equal distribution, with slightly higher rates for the middle quintiles.

The patterns in utilization are also reflected in the benefit incidence results. The benefit shares based on a standard BIA calculation with constant unit costs, as in equation (2), are presented for each type of healthcare service in columns 2, 6 and 10 of Table 2. The benefit shares based on district specific unit costs are presented in columns 4, 8 and 12. The standard benefit incidence share of hospital care for the wealthiest quintile increased over time, reaching 34 percent for inpatient care and 41 percent for outpatient care in 2017; whereas the shares for the poorest decline over time, to respectively 11 and 9 percent. Again, the standard benefit shares of primary care exhibit a much more equal distribution than hospital care.

Table 2. Distribution of healthcare utilization share across socioeconomic quintiles (2015-2017)

	Hospital Inpatient				Hospital Outpatient				Primary Care Outpatient			
	Contact per 100 individuals in one year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)	Contact per 100 individuals in one year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)	Contact per 100 individuals in one year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)
	1	2	3	4	5	6	7	8	9	10	11	12
2015												
Poorest	1.57	11.06	236.60	9.77	11.81	9.14	14.15	8.09	169.53	19.14	3.27	17.81
2nd quintile	1.94	13.44	243.00	12.23	15.74	12.32	14.76	11.46	181.69	20.53	3.44	19.80
3rd quintile	2.55	17.49	250.07	16.55	20.88	15.91	15.01	14.93	184.09	20.98	3.53	20.87
4th quintile	3.42	23.08	261.95	23.03	31.02	23.01	15.74	23.01	182.66	20.80	3.65	21.39
Richest	5.10	34.92	276.70	38.42	52.34	39.62	16.75	42.50	160.16	18.55	3.85	20.14
Mean	2.79	100	248.99	100.00	24.92	100	15.04	100.00	175.99	100	3.45	100.00
2016												
Poorest	1.52	10.31	223.54	9.24	12.17	9.46	14.02	8.42	156.30	18.92	3.46	17.60
2nd quintile	2.03	13.87	232.14	13.03	16.47	12.79	14.85	12.02	170.96	20.79	3.56	20.08
3rd quintile	2.52	17.29	233.66	16.32	20.13	15.72	14.98	15.13	171.26	20.77	3.67	20.47
4th quintile	3.56	24.41	243.49	24.29	28.86	22.70	15.25	22.41	175.59	21.27	3.76	21.82
Richest	4.98	34.12	256.08	37.12	50.31	39.33	16.09	42.01	150.72	18.26	4.03	20.02
Mean	2.93	100	235.13	100.00	25.64	100	14.91	100.00	164.89	100	3.60	100.00
2017												
Poorest	1.72	10.81	222.76	9.58	9.58	9.16	15.17	8.45	130.09	19.06	3.89	17.41
2nd quintile	2.34	14.70	234.03	13.84	13.48	12.76	15.45	12.16	138.32	20.08	4.01	19.10
3rd quintile	2.76	17.57	237.93	16.77	16.33	15.60	15.63	15.00	142.31	20.80	4.14	20.68
4th quintile	3.59	23.23	240.19	22.86	22.38	21.94	15.92	21.62	146.00	21.44	4.26	21.97
Richest	5.41	33.69	248.28	36.95	42.45	40.54	16.25	42.77	131.47	18.62	4.22	20.85
Mean	3.28	100	236.75	100.00	21.90	100	15.68	100.00	137.74	100	4.08	100.00

Source: Authors' calculation based on BPJS-*Kesehatan* claims data and SUSENAS 2015-2017. Note: Distribution of socioeconomic quintiles is based on per capita expenditure of each year (regional CPI adjusted).

3

When we allow for variation in the district unit costs, following equation (4), we see the discrepancy in benefit incidence of hospital care increases. For the wealthiest group the benefit share in 2017 increases to 37 percent for inpatient care, and to 43 percent for outpatient care. For the poorest the shares decrease even further, to 10 and 8 percent, respectively. A similar effect is observed for primary care. When we weigh the rather evenly distributed contact rates with the gradient in district specific unit costs, the resulting benefit incidence shares also turn pro-rich. The richest quintile now accounts for more than a twenty percent of the primary care spending, and the poorest quintile for 17 percent in 2017. This rise for the wealthier groups can partly be explained by JKN's gatekeeping mechanism, where referrals from community health centres are required for higher level care to be covered. According to Johar et al. (2018), there is an increasing use of GPs and primary health centres. Before JKN the better-off could directly consult a specialist or hospital without referral from a GP. But after the implementation of JKN and its gatekeeping mechanism, the requirement to obtain a referral from a primary care facility was more widely enforced.

3.5.3. National Unit Cost Vs. District Specific Unit Cost

The distributions of healthcare financing benefit incidence based on constant national average unit costs and district-specific unit costs are compared for 2017 in Figure 2 by means of concentration curves. We find that disparities in unit costs among districts generate a more pro-rich distribution. For all types of healthcare the concentration curves for district-specific unit costs are dominated by the curves for constant unit costs, as the latter lie closer to the diagonal across the income distribution indicating a more equal benefit incidence. The associated concentration indices therefore take a positive value and are larger for the district-specific unit cost benefit incidence, with the difference statistically significant at a 1 percent level for all types of care (significance tests of differences in the concentration indices are reported in Table B2).

Finally, the concentration curves for the benefit incidence of total healthcare funding, following equation (5), also show a clear pro-rich distribution (bottom-right graph in Figure 2). The concentration index is 0.178 when based on constant unit costs, but increases to 0.211 when we allow the unit costs to vary by district. These results suggest that provider payments of the JKN favour the wealthier groups and regions. Conversely, ignoring this regional variation in provider payments that is driven by initial disparities in healthcare supply, will underestimate the inequality in benefit incidence of healthcare spending. However, the concentration indices do not change much over time and these differences are not statistically significant, irrespective of whether we allow for variation in unit costs (the CI increases from 0.210 to 0.211 between 2015-2017, using district unit costs; detailed tests are reported in Appendix Table B3). This indicates that the regional inequality in JKN provider payments does not exacerbate the inequality in intensity and supply of healthcare (and thereby the benefit incidence) over time.

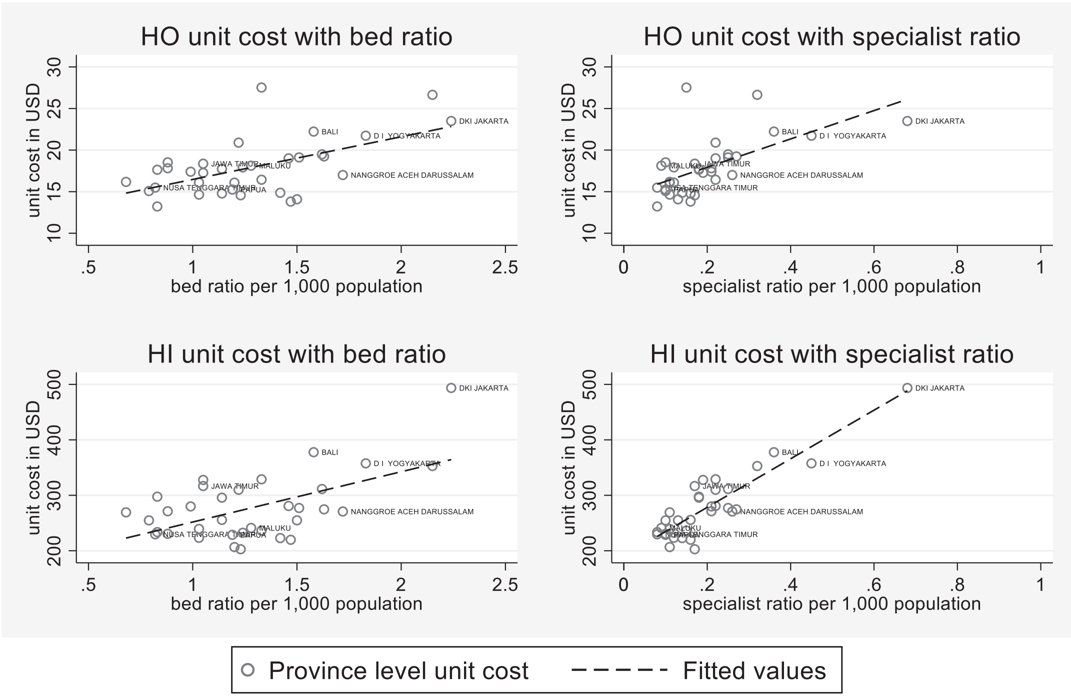
3.5.4. Healthcare financing benefit distribution based on geographic location

While we do not observe increasing inequities in benefit incidence over time as JKN was introduced, we do see a slight increase in disparities between and within regions. The urban share in healthcare expenditure was already larger than its 56 percent population share, and it increased very slightly from 64 to 66 percent between 2015 and 2017. The country's economically most developed islands Java and Bali represent around 57 percent of the national population yet benefit from around 67 percent of overall healthcare spending. This disparity is largely due to expenditures on secondary care. The benefit incidence of outpatient primary care remains equally distributed, although the urban share is growing slowly, from 53 to 56 percent (results reported in the Table B4). The rural share for the hospital inpatient benefit decreases slightly from 33 to 31 percent (See Appendix Table B4).

To assess changes in benefit incidence within regions we compute concentration indices for the main island groups and for the municipalities and rural districts. For the municipalities and the islands Java and Bali we see no statistically significant changes to the distribution of healthcare expenditure. However, for regions that were initially less endowed with healthcare supply, such as rural districts and the eastern islands (Maluku, Papua, NTT and NTB), we see a statistically significant increase in their concentration index value, suggesting an increased socioeconomic inequality in the benefit incidence (results reported in Appendix Table B5).

The disproportionate share going to the more developed regions can be explained partly by variation in unit costs. Figure 3 plots the average hospital care unit costs at province level against the average bed ratios and specialist ratios per 1,000 population. The scatterplots show positive correlations between hospital care unit costs and the availability of beds and specialists. This positive association reflects the fact that the JKN provider payment design favours regions with relatively abundant healthcare supply, thereby widening the gap in healthcare funding between regions.

Figure 3. Hospital care unit cost and healthcare facility availability at province-level (2017)



Source: BPJS-*Kesehatan* claims data for 2017 and Pusat Data dan Informasi Kementerian Kesehatan (2018)

Note: HO: Hospital Outpatient; HI: Hospital Inpatient; PO: Primary Care Outpatient.

3.5.5. Limitation

One key limitation of the Susenas data is that the number of outpatient visits is reported only in 2017. For 2015 and 2016 the survey only records whether a respondent obtained outpatient care and at what facility. For inpatient care, on the other hand, the Susenas records the annual number of inpatient days for all years. For consistency we therefore use the contact rate as a proxy for utilization, to calculate the benefit shares and the total spending benefit. Using the number of outpatient visits and inpatient days would be preferable. In order to check the sensitivity of our results to this simplification, we replicate the analysis with outpatient visits and inpatient days for the year in which the number of outpatient visits is available. The results are provided in Table B6 in the appendix. Two key observations emerge: (1) the gradient is slightly more pro-rich when we use utilization rates, but (1) the BIA results with constant and district unit costs are very similar. This confirms that our results are not affected by approximating utilization with the utilization fraction. We present these results in our paper, as we prefer a consistent approach for all years and types of care in order to calculate the overall benefit share.

We also note that we do not assess out-of-pocket payments in this study, despite the fact that these still commonly occur in Indonesia. Our analysis focusses on the implicit public subsidy transfer of health care utilisation and how this is distributed over the population. Out-of-pocket payments therefore fall beyond the scope of our paper.

Another caveat relates to the portability principle of JKN, which enables a patient to move to another hospital in a different district, province or island in case of a medical necessity. This implies that a district that receives a JKN disbursement is not necessarily the residence of the patient that received the treatment. Given the available data, we cannot adjust for cross-district-border healthcare utilization. However, a recent study of inter-province mobility based on the BPJS-Kesehatan claims data from 2015-2016 finds that inter-province patient movement is negligible compared to total JKN funding.[5]

Finally, we may still underestimate the inequality in the distribution of healthcare benefits as we are only using provider payments at district level and do not include geographic variation in unit cost of higher class hospital services (tertiary care), level of severity, and case-mix-groups of disease prevalence. For example, treatment for more costly diseases (such as cancer

[5] Center for Health Policy and Management, Gadjah Mada University (PKMK UGM). Study details can be accessed (in Bahasa Indonesia) at: https://kebijakankesehatanindonesia.net/datakesehatan/file/Portabilitas-peserta-JKN.html.

or cardiovascular disease) is likely to be relatively higher in wealthier urban areas and correlated with knowledge, health awareness and access to care.

3.6. Conclusion

Our research findings show that the benefits of healthcare spending since the introduction of Indonesia's JKN program are distributed disproportionately favouring the wealthier population groups, as well as urban areas and islands Java and Bali. We also find substantial variation in healthcare unit costs across districts, because regions with well-equipped health facilities are associated with relatively higher unit transfers for healthcare services.

This variation in unit costs implies that BIA using national average unit costs will underestimate the disparities in healthcare funding. Previous studies that have analysed healthcare utilization under JKN (and ignoring regional differences in unit transfers) are therefore likely to overestimate the extent to which JKN has reduced inequality in healthcare delivery.

A second implication of our BIA results is that we can interpret the difference in benefit incidence based on constant and varying unit costs as the bias inherent in JKN's provider payment mechanism: if the claims and capitation data were not biased towards wealthy regions and population groups, then any unequal distribution should be due to utilization patterns alone and the choice of unit costs should not matter. Nevertheless, we do not find statically significant changes to the CIs over time post-JKN, suggesting that JKN's provider payment system maintained initial disparities in treatment intensity and funding of healthcare between 2015 and 2017, but did not exacerbate these as some scholars had feared (Trisnantoro, 2019).

Two policy priorities emerge from our findings. First, to reduce inequities in healthcare funding across regions and population groups, the existing prospective payment mechanism would need to be modified using an affirmative or targeted design to promote higher value of care in regions with less-developed healthcare facilities. One possibility here to be considered is to adjust the InaCBG tariffs depending on supply readiness gaps. This might make health infrastructure investment more attractive in these areas. A similar instrument is already in use for primary care in the *Dana Kapitasi Khusus* policy that creates a higher capitation funding for primary care in remote districts (Ministry of Health, 2016a).

Second, the national and local governments could directly invest in the value of treatment and supply of healthcare facilities and staff in rural areas and districts outside Java and Bali. This is not an easy task, as witnessed by the same problem arising in many other countries. Especially difficult is attracting doctors and other medical personnel to work in remote places. Some inspiration can be obtained from the results of financial and non-financial incentives deployed in Thailand for medical school graduates to work in rural and remote areas (Wibulpolprasert & Pengpaibon, 2003). Similar policy suggestions have been provided by (Azwar et al., 1999). They concluded that offering specialist training may be a sufficient incentive to make doctors from Java willing to serve in remote areas, but that it is an expensive and potentially inefficient policy since specialist practice and rural public health management require different skills and attitudes. They claim that moderately (but not extremely) remote areas can also attract additional staff using modest cash incentives. They find that especially doctors originating from the Outer Islands are far more willing to serve in remote areas than their counterparts from Java. So, it may be worthwhile increasing the representation of Outer Island students in medical schools (perhaps through scholarships and assistance in pre-university preparation).

4

CHAPTER 4

Effects of performance-based capitation on the use of primary health care services in Indonesia

With Igna Bonfrer, Robert Sparrow, Menno Pradhan and Eddy Van Doorslaer

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Abstract

The Indonesian national health insurance agency BPJS Kesehatan, the largest single-payer system in the world, is among the first to combine capitation-based payments with performance-based financing. The Kapitasi Berbasis Komitmen (KBK) scheme for puskesmas (community health centres) was implemented in province capitals between August 2015 and May 2016. Its main goal was to incentivize the substitution of secondary by primary care use. We evaluate its effect on its three incentivized outcomes: the fraction of insured visiting the puskesmas, the fraction of chronically ill with a puskesmas visit and the hospital referral rate for insured with a non-specialistic condition. We use BPJS Kesehatan claims data from 2015 and 2016 from a stratified one percent sample of its members. Comparable control districts were identified using coarsened exact matching. We adopt a Difference-in-Differences (DID) study design and estimate a two-way fixed effects regression model to compare 27 intervention districts to 300 comparable non-capital control districts. We find that KBK payment increased the monthly percentage of enrolees contacting a puskesmas with 0.578 percentage points. This is a sizeable increase of 48 percent compared to the baseline rate of just 1.2% but it still leaves most puskesmas far below the "sufficient" KBK threshold of 15%. For chronically ill patients, a small increase of 1.15 percentage points was estimated, but it leaves the rate even further below the program's "sufficient" threshold of 50%. We find no statistically significant effect on referral rates to hospitals for conditions not requiring specialist care. While we find positive effects of KBK on two out of three outcomes, all estimated effect sizes leave the actual rates far below the program targets. Our findings suggest that the KBK performance-based capitation reform has not been very successful in substituting secondary care use by greater primary care use.

Keywords: Capitation; Pay-for-Performance; Health insurance; universal health coverage; Indonesia

4.1. Introduction

Indonesia's national health insurance scheme *Jaminan Kesehatan Nasional* (JKN) is the largest single-payer system in the world, covering a broad spectrum of primary to more advanced hospital care services (Agustina et al., 2019). JKN plays an important role in Indonesia's path towards Universal Health Coverage (World Health Organization, 2010) and provides a significant share of Indonesia's health care funding. It also has the potential to influence health care provider behaviour (Stein et al., 2020). The national Indonesian health insurance agency *Badan Penyelengara Jaminan Sosial Kesehatan* (BPJS Kesehatan) introduced *Kapitasi Berbasis Komitmen* (KBK), a performance-based financing scheme for primary care provided to JKN enrolees in 2016. The KBK was applied on top of the capitation payment program for community health centres (*Pusat Kesehatan Masyarakat* – Puskesmas) in 27 out of 34 province capitals for a total of 560 puskesmas (BPJS Kesehatan, 2015a). In 2014, a capitation scheme, moving away from earlier fee for service payments, was introduced and the performance-based element was added in 2015 (Presiden Republik Indonesia, 2013a). The goals of this performance-based capitation scheme were to improve accountability of puskesmas, promote better quality of puskesmas service delivery, and increase efficiency and effectiveness of Indonesia's national health insurance scheme (BPJS Kesehatan, 2015a). The expected shift from hospital to community health care should improve efficiency of spending in the health sector (Teplitskaya et al., 2021).

With the introduction of performance-based capitation, Indonesia joined policy makers from a range of low-and middle-income countries (LMICs) adopting financial incentives to change health care provider behaviour. While rigorous evidence on the effects of performance-based financing (PBF) schemes in LMICs, especially in Asia, remains scarce (Chalkley et al., 2020), the evidence base has slowly been expanding (Diaconu et al., 2021). PBF schemes adopted in LMICs are highly heterogeneous and cover a range of approaches (Diaconu et al., 2021).

Introducing performance-based financing (PBF) as a supplement to capitation-based payment is to our knowledge unique in the world, with only two exemptions. Plan Nacer in Argentina also combines capitation and PBF, specifically for maternal care delivery (Cortez, 2009). However, the capitation-based payments in Argentina were paid to provincial provinces by the National Ministry of Health, not directly to health care facilities (de Walque et al., 2022). The KBK performance-based capitation program also bares some similarities to China's Capitation Global Budget intervention to reduce antibiotic prescription (Yip et al., 2014) and improve prescription quality (Sun et al., 2016). However, China's global budget approach differs from capitation payment because the total annual budget based on among others number of hospitalizations has already been set at the beginning of the year and is therefore not directly dependent on the number of patients or insurance enrolees.

PBF as an independent mechanism, not linked to other payment routes such as capitation, has been implemented widely throughout low- and middle-income countries since the late 2000s. More than 2.5 billion USD has been invested in PBF projects in primary health service delivery in low-income countries (de Walque et al., 2022), but not as an add-on to a capitation based health care financing system as is the case in Indonesia. A recent report by the World Bank evaluating evidence on the effectiveness of independent or stand-alone PBF projects, suggests that performance pay has led to gains in primary health service delivery, but does not necessarily reduce gaps in physical infrastructure and availability of drugs and supplies (de Walque et al., 2022).

This study aims to evaluate the effects of KBK on its three incentivized monthly outcomes: the number of JKN insured patients with a visit to the puskesmas per 100 enrolees, the number of JKN insured chronically ill with a visit to the puskesmas per 100 enrolees and the hospital referral rate for insured with a non-specialistic condition. If the program has been successful, we would expect an increase in the first two outcomes and a decrease in the latter. To our knowledge, this is the first study to quantitatively evaluate the effects of the KBK program as it was implemented in province capitals. Most earlier evaluations of the KBK program have relied on case studies (Hasri et al., 2019; Widaty, 2017), adopted a qualitative approach (Aryani, 2022; Maharanti and Oktamianti, 2018; Widaty, 2017) or have not been peer-reviewed (Hidayat et al., 2017).

This study adds to existing knowledge by providing insights about the effectiveness of a combined PBF and capitation based health care system which might address some of the shortcomings of a stand-alone PBF intervention. The latter tends to have limited effectiveness when the existing health care system has no operating budget provided to frontline health facilities (de Walque et al., 2022). With a capitation based system, we would expect funding to be in place to ensure availability of a basic facility structure and equipment. Using this facility and equipment, performance-based incentives can motivate health care providers to deliver effective services. Furthermore, contrary to the majority of earlier work on PBF, this study focuses not on maternal and child health services but on primary care provision in general, also for chronically ill patients.

Background

Indonesia is a large middle-income country with 270.2 million inhabitants and a modest economic growth. Between 1960 and 2001, the medical care infrastructure grew from virtually no primary health care to 20.900 facilities (Agustina et al., 2019). With the introduction of JKN, the National Health Insurance System, more than 80 percent of the total Indonesian population has now gained coverage (BPJS Kesehatan, 2019). Approximately 12.000 primary health care providers participate in the JKN program and about three quarters of these are puskesmas (Ariawan et al., 2019). The other 25 percent primary care facilities are general practitioners and private clinics. Indonesians not participating in JKN, pay their health care expenditures out-of-pocket (Nugraheni et al., 2020). In some cases, patients paying out-of-pocket are prioritised for inpatient beds, leading to shorter waiting times for this select group (Mahendradhata et al., 2017). Public doctors can have a dual practice, also providing private care on a fee-for-service basis for non-JKN enrolees after their working hours in public facilities, which can result in some cases in substandard performance of providers in the public facilities (Gonzalez et al., 2017).

Puskemas provide primary care and act as gate-keepers for all health care services in Indonesia (Stein et al., 2020). Primary care services in Indonesia face challenges in providing quality health services (Bappenas/Kementerian PPN, 2019) including a wide rural-urban gap in supply-side readiness (World Bank, 2018) and wide variation in catchment populations ranging in size from 2,000 to about 98,000 JKN enrolees (World Bank, 2018). While JKN enrolees can choose their primary care provider, they cannot seek care at higher-level healthcare facilities, such as hospitals, without a referral (Stein et al., 2020) unless they pay out-of-pocket. Emergency care is exempted, enabling JKN enrolees to directly go to any hospital (Presiden Republik Indonesia, 2013b).

In 2015, BPJS Kesehatan funding accounted for more than half of the total budget of puskemas, supplemented with funds from local governments and donors (World Bank, 2018). The average revenues per puskesmas increased from 22.000 USD in 2013 to 81.000 USD in 2015 (Appendix Table C1). Hospital care accounted for 82 percent of total JKN expenditure in 2015, primary care for 17 percent and the remaining 1 percent is for health promotion activity.

The KBK performance-based capitation for primary care providers was accompanied by a reform of the referral system to improve efficiency and effectiveness of service delivery and access to health services (Agustina et al., 2019). Rising costs at the hospital level for avoidable advanced care provided one of the main rationales for BPJS Kesehatan to introduce financial incentives for community health centres (BPJS Kesehatan, 2016a). These incentives aimed to encourage more contacts between users and primary care providers, increase the number of primary care visits for chronically ill and discourage hospital referrals for a subset of so-called "non-specialistic" conditions, which should fall within the standard competency of general practitioners (Indonesian Medical Council, 2012) such as asthma, tuberculosis and dengue (BPJS Kesehatan, 2016b). The underlying assumption was that by strengthening the gate keeper mechanism for chronically ill in primary care facilities, a share of hospital care can be avoided, for example through the effective management of hypertension and diabetes mellitus type 2 (BPJS Kesehatan, 2014). In addition to avoiding unnecessary hospital care through increased primary care provision, the lower case load for hospitals was expected to reduce waiting times and improve quality (Agustina et al., 2019). The intervention was also anticipated to increase financial accountability of primary care providers and local governance (Indonesian Corruption Watch, 2018).

Study setting

From December 2014 to May 2015, BPJS Kesehatan implemented a performance-based capitation pilot for community health centres providers serving JKN enrolees in 62 puskesmas in Padang, Pekanbaru and Jambi. All puskesmas in Padang and Pekanbaru received the intervention, and puskesmas in Jambi served as control district. During the first month of the pilot, health care utilization in the intervention group did not differ significantly from the control group. After six months, utilization in the intervention facilities did increase and reached the predetermined targets (contact rate, non-specialistic referral rate, proportion of facility's enrolee transfer to other primary care provider and chronic disease patients visit rate) (BPJS Kesehatan, 2015b). These promising results provided the impetus to develop and implement an adjusted version of the KBK scheme (BPJS Kesehatan, 2015c) that was implemented in province capitals, and which is the focus of this study.

KBK was implemented in province capitals, non-randomly and stepwise between August 2015 and May 2016, with the majority of districts joining the program in January 2016. A province capital is a district that is determined by national government as a capital where the governor's office and other province institution are located. Local district governments decided when their puskesmas joined the KBK program. Table 1 shows the timing of KBK implementation by district. BPJS Kesehatan published the nationwide "Regulations on KBK implementation" on the 28th of July 2015 (BPJS Kesehatan, 2015a) containing the three incentivised outcomes with the associated targets and malus/bonus percentages. Following the pilot, the BPJS Kesehatan's first plan was to introduce KBK for 995 puskesmas (out of 9,345 JKN registered puskesmas) catering for JKN enrolees in 33 out of 34 province capitals (BPJS Kesehatan, 2015a, 2015d) on 1 August 2015. However, as some of the capital cities were not ready, the timing was relaxed and the province capitals were allowed to start KBK by 1 January 2016 (BPJS Kesehatan, 2015d). From 2017 onwards the KBK program was implemented nationwide, limiting the opportunities to evaluate the effects of the program in the absence of a comparable control group. This study evaluates the implementation of KBK in province capitals, after the pilot and before the nationwide rollout.

The intervention group consists of 30 out of 34 province capitals. Padang (West Sumatera) and Pekanbaru (Riau) participated in the pilot, while Surabaya (East Java) only implemented KBK in 2018, after the nationwide roll out, so these cities are excluded from the treatment group. Surabaya was added as potential control district but was not selected based on our matching criteria. In addition, the districts in the Special Capital Region of Jakarta, the nation's capital, are also excluded because of structural wage difference with other cities in Indonesia (Badan Penelitian dan Pengembangan Kesehatan, 2018) and KBK is therefore unlikely to significantly impact puskesmas staff income in Jakarta.

Table 1: Timing of KBK implementation

Capital City	Province	Start KBK implementation
Jayapura	Papua	August 2015
Tanjung Pinang	Riau Islands (Kepulauan Riau)	September 2015
Jambi	Jambi	September 2015
Bengkulu	Bengkulu	October 2015
Batam	Riau Islands (Kepulauan Riau)	November 2015
Pangkal Pinang	Bangka Belitung	December 2015
Sorong	West Papua	March 2016
Banjarmasin	South Kalimantan	May 2016
Other 22 capital cities	Other 23 provinces	January 2016

Source: (BPJS Kesehatan, 2021a)

The KBK program used three performance indicators, as shown in Table 2. The "contact rate" reflects the fraction of JKN enrolees that used primary health care at least once in a specific month (Ministry of Health and BPJS Kesehatan, 2017). This includes care provided on an individual basis in community health centres as well as during public health promotion gatherings outside the puskesmas. For a facility to perform "sufficiently", the contact rate is required to be at least 15 per 100 registered JKN enrolees in a facility in a given month. For "excellent" performance the threshold was at least 25 per 100 enrolees. The second performance indicator, the "chronic disease contact rate", reflects the fraction with at least one monthly visit to the puskesmas for the subset of JKN enrolees with hypertension and/or diabetes mellitus type 2. These two diseases were selected by BPJS Kesehatan as tracer conditions since these are two leading causes of death and disability in Indonesia (BPJS Kesehatan, 2014; IHME, 2019) that generate the highest disease burden among JKN enrolees (Mahendradhata et al., 2017). Sufficient and excellent performance are reached with respectively 50 and 90 out of 100 chronically ill enrolees visiting the puskesmas at least once per month. The third incentivised outcome is the "non-specialistic referral ratio" which is based on a referral structure that identifies a total of 144 diagnoses for which primary care providers are considered competent to provide the necessary care and should therefore not be referred to secondary care (BPJS Kesehatan, 2015a). A puskesmas does not reach the "sufficient" threshold when more than five percent of the overall number of referrals in the facility that month relate to non-specialistic patients i.e. those with a diagnosis from the list of 144 diagnoses. For the excellence threshold, this should be less than one percent.

Table 2 KBK monthly performance indicators

	Sufficient	Excellent
Contact rate	> 15 per 100	> 25 per 100
Chronic disease contact rate	> 50 per 100	> 90 per 100
Non-specialistic referral rate	< 5 per 100	< 1 per 100

Note: (BPJS Kesehatan, 2015a)

The monthly bonus or malus was dependent on the share of performance indicators reached at either sufficient or excellent level. Table 3 shows the percentage of the capitation amount paid out to puskesmas based on their performance on each of the three indicators. Puskesmas not meeting at least the sufficient target for any of the three performance indicators incurred a 25 percent malus on their capitation-based payment. Facilities performing excellent on all three indicators received a 15 percent bonus on their capitation payment.

Table 3 Performance-based capitation payout based on number of performance indicators meeting the thresholds

Not sufficient out of 3	Sufficient out of 3	Excellent out of 3	Percentage of KBK capitation paid out
3	0	0	75%
2	1	0	80%
1	2	0	90%
0	3	0	100%
0	2	1	105%
0	1	2	110%
0	0	3	115%
2	0	1	90%
1	1	1	95%
1	0	2	98%

Source: (BPJS Kesehatan, 2015a)

The base capitation amount is determined by the number of registered JKN enrolees in a facility (Presiden Republik Indonesia, 2014) amounting to 6,000 Indonesian Rupiah (IDR) or 0.46

USD per enrolee per month for puskesmas with at least two medical doctors (see Appendix Table C2). Payments are made directly to a specific puskesmas. BPJS Kesehatan uses a non-capitation or claim scheme for maternal delivery, immunisation, and inpatient services.

BPJS Kesehatan regulates the allocation of capitation payments from puskesmas to health staff and operational activities. The minimum allocation for health staff is 60 percent from the total capitation amount received by puskesmas. The share of operational cost depends on the total capitation minus the share paid to health staff. The allocation is determined by the district regent (Bupati) or major (Walikota). The allocation of funds to the health staff depends on the type of health staff (general practitioner, nurse, midwife, pharmacist), level of education, working experience as well as the attendance of the health staff in that month (Ministry of Health, 2016).

To avoid gaming, BPJS Kesehatan introduced a Monitoring and Evaluation (M&E) team and an Assessment team in each local BPJS Kesehatan office. The M&E team monitors progress in facilities in response to the KBK introduction and assessed "service commitment fulfilment". Based on random unannounced visits to facilities, the M&E team aims to reduce fraud and provides recommendations and suggestions for program improvements to BPJS Kesehatan (BPJS Kesehatan 2015). The assessment team facilitates monthly data entry and processing to determine bonus and malus percentages for each facility based on the performance indicators (Table 2).

4.2. Data

We use BPJS Kesehatan claims data from a stratified one percent sample of JKN household members, covering health care use between January 2015 and December 2016 (Ariawan et al., 2019; Hidayat, 2019). These data cover seven months before and seventeen months after the KBK announcement. However, the actual implementation start date differs for some districts (see Table 1). We calculate monthly district averages over a total of 24 months using claims data from 817,552 JKN insurance enrolees in 327 districts (27 out of 34 province capitals and 300 control districts).

The one percent sample data are representative at national, province and district level (Ariawan et al., 2019). Further details can be found in Fuad (Fuad, 2019) and the BPJS Kesehatan data sample manual (Ariawan et al., 2019). The subsample is obtained as a stratified random draw executed by BPJS Kesehatan in three strata: Category 1 individuals who never filed any claims for health care i.e. "non-users", Category 2 individuals who claimed only primary care i.e. "primary care users", and Category 3 those who claimed both primary and hospital care i.e. "primary and hospital care users". For each puskesmas, ten households were randomly drawn from each of the three categories. We know for each claim in which district health care was used but we do not observe which specific puskesmas, from a total of 22,024 primary care facilities, provided the care.

BPJS Kesehatan provides individual weights to make the sample data representative of the JKN enrolees population. The household weights are obtained by dividing a facility's JKN enrolee population by the ten households sampled for each of the three categories. The individual weight is the household weight divided by the household size (Ariawan et al., 2019). We multiply this individual weight with the health care used based on the claims data from that JKN enrolees. Appendix Table C3 shows an example, using hypothetical data, of the calculation of the individual weights for each of the three categories by BPJS Kesehatan.

One limitation of our data is that BPJS Kesehatan stratified the household sampling at the end of the observation period. While the weighting process for our data may be correct for the last month, i.e. December 2016, it is possible that in January 2015, only a subset of the 30 households per facility were already JKN enrolees. Some households may have joined later, especially given that enrolment was increasing over the study period. Therefore, the weights may potentially lead to a downward bias of our contact rate estimates since the usage in earlier months in that district is not fully captured.

We include 77.3% of JKN enrolees registered at puskesmas (Ariawan et al., 2019). We only use claims data for health care utilization in puskesmas and exclude primary care provided by other providers such as general practitioners (GPs) and private clinics since these were not included in the KBK scheme. Visits to private clinics and GPs accounted for 33.7% and 14.5% of total visits respectively. We include all available claims of individuals from Categories 2 and 3 households using care in a puskesmas. We use the JKN enrolees hospital admission data to identify referrals for individuals in Category 3 from puskemas to hospitals. We subsequently aggregate utilization data to district level so we can compare districts that applied KBK to non-KBK district. We cannot use individual level data because we only have access to the one percent sample and do not know in which Puskesmas an individual was enrolled. Using district level data allows us to compare district average outcomes to the KBK targets. We assume the district average is representative of the performance of puskesmas within that district.

Control group

The KBK assignment is non-random, through a step-wise roll out across province capitals. We applied Coarsened Exact Matching (CEM) (Iacus et al., 2012) to identify control districts that are most similar to the province capital districts. The main advantage of CEM over other matching methods such as Propensity Score Matching (PSM) is that it reduces model dependency. CEM improves balance for a covariate without reducing balance for another covariate, and automatically restricts estimates to those on common support. CEM also allows for ex-ante informed decisions about which matching criteria are most fitting (e.g. covariates, thresholds) (Iacus et al., 2012). CEM does imply a trade-off between bias and precision: more matching strata is likely to reduce bias due to differences between intervention and control group but also reduces the number of observations in the subsequent analyses.

We include three matching variables in the CEM, all at baseline in 2015, reflecting both puskesmas and district characteristics: average puskesmas size, puskesmas enrolee per doctor ratio and average capitation payment per JKN enrolee. Ideally, our baseline reference period is January-July 2015, i.e. before August 2015. However, since we could not obtain reliable data for this period on puskesmas at district level we had to resort to data from the Ministry of Health and BPJS-Kesehatan for December 2015. Average puskesmas size is the total number of JKN enrolees per district divided by the number of puskesmas in that district (Ariawan et al., 2019; Ministry of Health, 2015). The puskesmas enrolee per doctor ratio is the number of JKN enrolees in a district divided by the number of doctors working in all puskesmas of a district (Ariawan et al., 2019; Ministry of Health, 2015). Finally, the capitation obtained per

JKN enrolee is derived from the total capitation received by a district divided by the number of JKN enrolees in that district (BPJS Kesehatan, 2017). The latter covers capitation for not only puskesmas but all primary care providers in a district since more detailed data are not available. We use the standard Sturge's rule (Iacus et al., 2021) to define bins for the capitation per JKN enrolee criteria. We set the bins at 0-3500; 3501-5000 and 5001-10,000 IDR for the capitation per JKN enrolee in line with the thresholds defined for capitation based on puskesmas' characteristics (see Appendix Table C2). This results in 27 out of 30 districts matched to a total of 300 out of 437 control districts, see also Appendix Table C4. We check the robustness of results to only allowing for control districts that are located in the same province as the intervention district.

4.3. Methods

Outcome measures

We estimate effects on three outcomes that proxy the three KBK monthly performance indicators (see Table 2) i.e. the contact rate, the chronic disease contact rate and the non-specialistic referral rate. The contact rate used in the KBK scheme includes both individual visits to a primary care provider and participation in public health promotions through larger gatherings. The latter events do not result in separate individual claims and are therefore not observed in our dataset.

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We define CP_{kt}, as the percentage of JKN enrolees registered in puskesmas with at least one visit in a month, and refer to this as the contact percentage. This outcome measure is derived from VM_{kt} which denotes the number of enrolees in a district k who visited a puskesmas in month t by multiplying each enrolee with a least one visit with its individual weight. Then, the total number of enrolees who visited at least once in month t is divided by the puskesmas enrolees size PM_{kT} in district k at the end of the study period (T, December 2016). The denominator is constant over time because we assume that the sample of enrolees remains the same between 1st January 2015 and 31st of December 2016. The resulting fraction is multiplied by 100 to obtain an estimate per 100 JKN enrolees, to allow comparison to the KBK monthly performance indicator. Equation 1 describes the percentage with a monthly visit.

$$CP_{kt} = \frac{VM_{kt}}{PM_{kT}} \text{ x } 100 \qquad (1)$$

The second outcome measure, the chronic disease contact percentage ($CDCP_{kt}$) in district k at month t, as shown in Equation 2, is estimated using the number of visits for individuals diagnosed with diabetes mellitus type II and hypertension, as indicated in the KBK guidelines (BPJS Kesehatan 2015). If an enrolee visits the puskesmas multiple times in a month, this is counted as one. To estimate the total number of enrolees with chronic disease visits, CVM_{kt}, we multiply each visit to a puskesmas by a enrolee diagnosed with hypertension and/or diabetes type 2 in a month with the associated individual weight. This results in an estimation of the number of visits as part of the Chronic Disease Management Program *Prolanis*. Prolanis includes activities to support JKN enrolees with a chronic disease by proactively involving participants, health facilities and BPJS Kesehatan (BPJS Kesehatan, 2021b). Next, we divide the aggregate number of visits for diabetes type 2 and hypertension by the estimated *Prolanis* enrolees in a district. The BPJS Kesehatan data from the stratified one percent sample is largely representative of the population data on incidence of hypertension and diabetes type 2 (Husnayain, 2020), justifying our use of individual weights. Husnayain (2020) analysed BPJS Kesehatan sample data using individual weights and found that the data for chronic diseases, malaria, and dengue are representative at the district level compared to population data on incidence. Because the number of puskesmas enrolees categorised as *Prolanis* participants per district is not publicly available, we estimate a puskesmas's total number of adult enrolees with diabetes type 2 or hypertension in a district $PCDM_k$. This is the share of the population aged 18 years and older in a district multiplied by the total number of puskesmas enrolees in a district i.e. the combination of adults and children in the one percent sample data, subsequently multiplied by the national prevalence rates of hypertension and diabetes type 2 (9.5% and 1.5% or equal to 11% for both diagnoses combined (Ministry of Health, 2018). The BPJS Kesehatan set 50 contact per 100 Prolanis enrolees per month as the "sufficient" performance target and 90 per 100 Prolanis enrolees as the "excellent" target (see Table 2).

$$CDCP_{kt} = \frac{CVM_{kt}}{PCDM_k} \times 100 \qquad (2)$$

The third and final monthly performance indicator of the KBK program is the non-specialistic referral rate $NSRR_{kt}$ in district *k* at time *t* as shown in Equation 3. The $NSRR_{kt}$ is estimated based on all referrals related to the 144 non-specialistic diagnoses identified within KBK for which primary care providers are considered competent to provide the necessary care and should therefore not refer to secondary care. Unlike the data on puskesmas visits, these data are derived from the JKN enrolees hospital admission data. Each non-specialistic referral is multiplied with the individual weight, as also used for the puskesmas contact percentage, to obtain the district k aggregate in month t. The total number of non-specialistic referrals from puskesmas, NSR_{kt} is divided by TR_{kt} the total number of referrals in a district

k in month t.

$$NSRR_{kt} = \frac{NSR_{kt}}{TR_{kt}} \text{ x } 100 \qquad (3)$$

Model Specification

Initially, the KBK reform was targeted to province capitals only. This selection is indeed a source of endogeneity because of the non-random roll out of the KBK. Both the targeting (only province capitals) and the timing of implementation (based on district readiness) are not exogenous. Since the targeting is based on time-invariant pre-intervention criteria (i.e. being a province capital ready to implement), our key strategy to identify causal effects is to compare treated and control districts over time.

The main threat to the parallel trend assumption comes from unobserved time-varying confounders. While we cannot completely rule these out, we can assess the credibility of our strategy by comparing the pre-intervention trends for treated and controls in the 7 months before KBK was announced (Dimitrovová et al., 2020). We see very similar patterns during this period. In addition, applying CEM further reduces initial imbalances (in particular for monthly visits and chronic diseases visits, where the weighted pre-trends are almost identical for treated and controls), increasing the likelihood that the parallel trend assumption holds.

To estimate the effect of KBK we adopt a two-way fixed effects regression model to compare province capital (intervention) districts (n = 27 covering a total of 560 puskesmas) to matched non-capital (control) districts (n = 300 covering a total of 5,696 puskesmas) to estimate monthly effects on the three incentivized outcomes (Wing et al., 2018).

We estimate two models. The first model considers the effect of the KBK announcement on 28 July 2015, where the KBK announcement variable $KBK(Announcement)_{kt}$ equals 1 for each month starting from 1 Aug 2015 to 31 December 2016 (17 months) for KBK districts:

$$Y_{kt} = a_k + b_t + \delta KBK(Announcement)_{kt} + \varepsilon_{kt} \qquad (4)$$

The district level outcome variable of interest, Y_{kt}, is either the number of monthly contact percentage CP_{kt}, chronic disease contact percentage $CDCP_{kt}$ or non-specialistic referral rate $NSRR_{kt}$. The district fixed effect a_k represents the combined effect of all time-invariant characteristics of district k, b_t represents the time fixed effects, and ε_{kt} is a random error. Lastly, δ is the effect of KBK announcement.

In the second model, we aim to split the impact of KBK into an anticipation and an implementation effect, by separately including two treatment effects, $KBK(A)_{kt}$ and $KBK(I)_{kt}$:

$$Y_{kt} \quad = a_k + b_t + \beta_1 KBK(A)_{kt} + \beta_2 KBK(I)_{kt} + \varepsilon_{kt} \qquad (5)$$

The anticipation variable $KBK(A)_{kt}$ equals 1 for each month between 1 Aug 2015 and the district specific implementation date. Thus, while this anticipation period equals 5 months for most districts (with starting date 1 January 2016), it varies from zero months (for early adopter Papua) to ten months (to late adopter South Kalimantan) (see also Table 1). The treatment variable $KBK(I)_{kt}$ takes value 1 if district k has actual implementation of KBK in month t and zero otherwise. Thus, β_1 captures the anticipation effect of KBK announcement, while β_2 identifies the treatment effect of KBK implementation. The announcement effect δ in equation 4 is then a weighted average of these two effects. All analyses were performed using STATA, version 16.

4.4. Results

Balance of characteristics

Table 4 presents descriptive statistics of outcome variables and baseline characteristics for both treated and control districts. Overall, on average, KBK districts show a significantly higher contact percentage and a lower non-specialistic hospital referral rate at baseline. The differences in contact percentage may indicate a healthcare access gap between treated and control districts. Province capitals are more likely to have infrastructure that allows easier access to puskesmas compared to more rural areas. Meanwhile, the non-specialistic referral rate in KBK districts is lower since its puskesmas may have more capacity to handle non-specialistic cases (Putri, 2019). The summary statistics at baseline also indicate that treated districts have a larger average puskesmas size, higher capitation per JKN enrolee and a lower enrolee to puskesmas GP ratio. Suggesting that puskesmas GPs in KBK districts may be less burdened by the volume of patients coming to their facility.

Table 4. District level summary statistics by KBK Status at baseline (2015)

	Without Matching			After Matching		
	KBK	Non-KBK	Difference KBK – Non KBK (t-test)	KBK	Non-KBK	Difference KBK – Non KBK (t-test)
Number of Observations (district x month)	360	4,835		321	2,627	
Outcomes						
Contact percentage	1.17	0.99	0.17***	1.21	1.04	0.16**
Chronic diseases contact percentage	1.26	0.93	0.33***	1.32	1.01	0.31***
Non specialistic referral rate (%)	18.68	25.16	-6.48***	18.95	25.16	- 6.21***
District characteristics						
Number of Observations (district)	30	469		27	300	
District average puskesmas size	16,283	13,215	3,068*	15,371	13,023	2,348*
Puskesmas enrolees per doctor ratio	7,799	12,213	-4,414	7,638	9,100	-1,462
Capitation IDR disbursed per JKN enrolee per month	5,818	6,388	-570	6,165	5,716	449

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The number of puskesmas and doctors per district are obtained from the Ministry of Health (2015). The amount of capitation originates from BPJS Kesehatan unpublished data (BPJS Kesehatan, 2017).

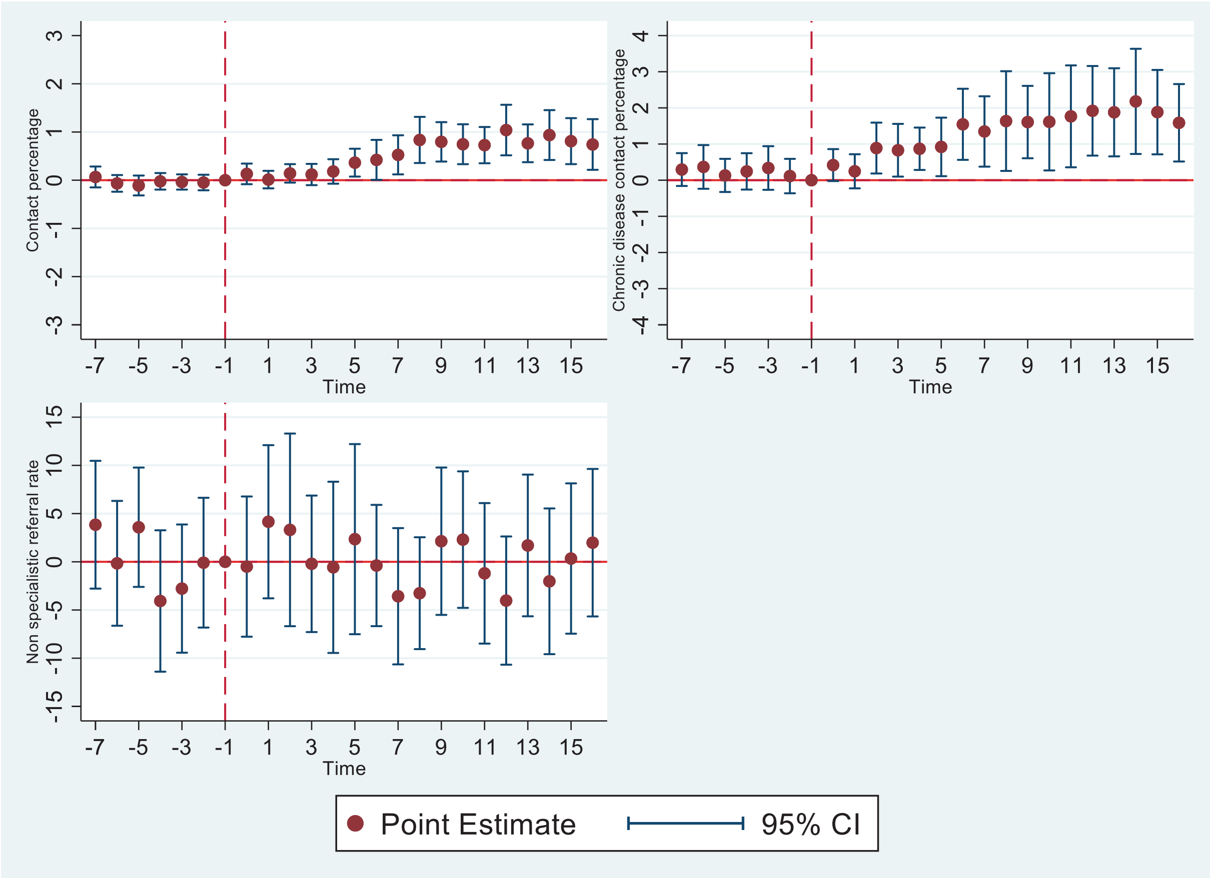
While Table 4 reveals some statically significant differences in outcomes and characteristics at baseline between KBK and matched non-KBK districts, Figure 1 shows that the trends in contact percentage and chronic disease contact percentage were parallel up to July 2015 (month = -1), just prior to KBK announcement. The time trends for the non-specialistic referral rate show a more erratic pattern.

For a more informative graphical illustration of our treatment effects, we present a standard event study graph in Figure 2 with the month-specific effects of announcement – estimated from a modification of equation (4) where the treatment variable is replaced by the interactions between the KBK treatment group and month dummies. The figure shows the estimated coefficients and their confidence intervals by creating lead and lags from the month that was KBK announced (month -1). In line with Figure 1, the results support the parallel trend assumption, as the coefficients are stable near zero for the period -7 to -1, and then slowly increase during the 17 months after KBK announcement for the contact percentage and chronic disease contact percentage. These results are consistent with the estimates of Model 2 (equation 5) where the anticipation effect is identified as the treatment effect observed between the time of announcement and implementation of KBK.

Figure 1. Coarsened Exact Matching weighted outcomes – months away from KBK announcement

Source: BPJS Kesehatan sample data (2015-2016).

Figure 2. Event study graph of the announcement effect and confidence intervals of KBK per month



Note: Event study leads and lags coefficients estimates for each KBK targeted outcome and 95% confidence intervals. We use month -1 (July 2015) as the reference month.

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There are two factors that may explain the anticipation effect from August 2015 onwards. First, BPJS Kesehatan performed a pilot study of KBK, the results of which were published in June 2015 (BPJS Kesehatan, 2015c). In that same period, BPJS conducted a workshop about KBK in 12 provinces preceding implementation of performance-based capitation (BPJS Kesehatan, 2015c). Second, the detailed KBK regulations were already made public on 28 July 2015 (BPJS Kesehatan, 2015a).

Impact estimates

Table 5 reports estimation results of the two-way fixed effects regression models. The first panel reports estimates for a conventional difference-in-difference model using the August 2015 announcement as treatment (equation 4). The second panel reports the separate estimates for anticipation (from August 2015) and implementation (from the actual implementation date). The results are consistent across both models, suggesting positive impacts for contact percentage and chronic disease contact percentage, but not for non-specialist referral rate. As expected, the combined effect from equation (4) appears to be a weighted average of the anticipation and implementation effects from equation (5). There is clear evidence of a significant anticipation effect. Based on the estimation results, we conclude that KBK implementation raised the contact percentage by 0.735 points, following an anticipation effect of 0.146 percentage points (Equation 5). Combined, this caused an increase of 0.578 percentage points since the announcement of the KBK (Equation 4),

The KBK effects are positive for the contact percentage and the chronic disease contact percentage (p-value < 0.10), in line with the intention of the program. The non-specialist referral rate does not appear to have been affected, as neither of the effect estimates is statistically significant. Compared to baseline values, the monthly contact percentage increased by about 48% due to the announcement of KBK. While this may sound like a large relative rise, a 0.578 increase from the baseline rate of 1.21 per 100 enrolees per month in 2015 is still very far below the target rate of 15 per 100 enrolees. The chronic disease contact percentage shows a relative increase of 1.15 per 100 chronically ill enrolees as a result of KBK while the non-specialistic referral rate effect is far from statistically significant. We checked the robustness of our findings from our main model (equation 4) to the use of different matching regimes to identify the control group (see Appendix Table C5) i.e. no CEM weights, CEM allowing for only one exact match, CEM weights while also requiring control districts to be in the same province as the intervention district and the latter while also allowing only one exact match. These robustness checks do not qualitatively change the findings of our study.

Table 5. KBK effect estimates from CEM weighted two-way fixed effects regression model with announcement starting from August 2015 compared to separate anticipation and implementation estimates

		CEM Weighted DiD		
		(1)	(2)	(3)
		Contact percentage	Chronic disease contact percentage	Non specialistic
Sufficient threshold		15	50	5
Baseline value		1.21	1.32	18.95
Model 1	KBK (announcement)	0.578***	1.149***	0.101
		(0.0534)	(0.147)	(1.084)
	N	7,795	7,795	7,334
Model 2	KBKI (actual implementation)	0.735***	1.377***	-0.340
		(0.165)	(0.402)	(1.402)
	KBKA (anticipation)	0.146**	0.520***	1.320
		(0.0646)	(0.161)	(2.004)
	N	7,795	7,795	7,334

Notes: robust standard error in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01. Monthly dummies and district dummies are not presented. Model 1 refers to Equation 4, Model 2 to Equation 5. N = 327 of which 27 KBK and 300 non-KBK.

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4.5. Discussion

The national Indonesian health insurance agency *Badan Penyelengara Jaminan Sosial Kesehatan* (BPJS Kesehatan) introduced *Kapitasi Berbasis Komitmen* (KBK), a performance-based financing scheme for primary care providers in province capitals in 2016. This health care financing scheme is unique because it combines existing capitation-based payments with performance-based payouts. We estimate the impact of the KBK program on primary care utilization and hospital referrals and find that effects on the two incentivized outcomes are statistically significant (monthly contact percentage and chronic disease contact percentage) and in the intended direction. However, while the magnitudes of the treatment effects are substantial relative to the counterfactual, the KBK did not manage to bring these anywhere close to the target rates with only around ten times as small as the objective. Our findings are similar to those of Hidayat et al. (2017) who used puskemas level BPJS Kesehatan data, as opposed to our district level estimates, to estimate KBK effects. They find significant but modest effects on contact rate and chronic disease contact rate, but not on the non-specialistic referral rate, in line with our findings.

We hypothesise five reasons why the KBK intervention seems to have failed to achieve its objectives. First, the KBK targets seem to have been set unrealistically high for the providers to meet given current capacity constraints. With inadequate staff levels and multitasking problems, most puskesmas cannot cope with almost 15 monthly visits per 100 enrolees per month. A puskesmas self-assessment performed in 2017 suggested that only about 33% of all puskesmas had the capacity to provide services according to the minimum standards (Bappenas/Kementerian PPN, 2019). Further, Fuady (2019) argues that the preparation in province capitals for the KBK rollout caused controversy since its implementation was done quickly, without much consideration of readiness and with considerable variability of facility readiness. Fuady (2019) also mentions the lack of communication with the Indonesian Medical Association (Indonesian Medical Association, 2015).

Second, the underperformance in KBK targets may be due to the wide variation in reporting knowledge and managerial capacity in puskesmas. Widaty (2017) highlights the technical problems incurred in the online reporting to BPJS Kesehatan system through P-Care, an information system that created for primary care providers to record JKN enrolees health condition and utilization (Kurniawan et al., 2017). A qualitative assessment held in March 2017 suggests that Primary care facility staff in Surabaya (East Java) often experienced errors in BPJS online application (Widaty, 2017).

Third, if an enrolee has already had a contact at a puskesmas in a specific month, there is no financial incentive to provide any further primary care to that that month. There is also no financial incentive for private care users to switch to a puskesmas. In an urban setting, a private clinic is more accessible because it is usually open after office hours while this is not the case for puskesmas. Our exercise using the National Socio-Economic Survey 2016 also show that larger districts record greater use of the private primary care, but the difference is modest. Another possible pathway is that JKN enrolees registered at a puskesmas can still substitute care by going elsewhere i.e. to a GP or private clinic using their JKN enrolment. We found such substitution to take place only very infrequently: 2.7% and 4.17% of puskemas enrolees also use private clinics and GP practices, respectively. As a result, such private utilization is unlikely to significantly affect our effect estimates.

Fourth, the additional incentive from the KBK program cannot always be paid out to health care facilities because of financial bureaucracy creating a barrier effectively setting an upper and lower bound on the capitation. The Ministry of Health restricts the capitation tariff to the range of 3,000 – 6,000 IDR per enrolee per month. This implies for example that certain puskesmas scoring “excellent” on all three indicators do not receive the expected 6,900 IDR per enrolee per month but only the maximum of 6,000 IDR. Also on the other side of the spectrum, low performing puskemas under the KBK program, will not receive less than 3,000 IDR per enrolee per month even when they do not reach any of the predefined KBK targets while this should in theory result in only 2,250 IDR per enrolee per month. This discrepancy suggests that the KBK regulation from BPJS Kesehatan has not (yet) been aligned with the the financial regulations on payment standards set by the Ministry of Health (Ministry of Health Regulation Number 52 Year 2016 on Standard Tariff for Health Service on JKN).

Fifth, incentives provided to puskesmas under KBK might not or insufficiently be passed on to individual health care providers (Widaty, 2017) given that (a minimum of) 60 percent of total capitation flows to health workers, diluting the direct incentive.

Our analysis is subject to various limitations. The first limitation is that, due to data constraints, our estimates do not include healthcare promotion meetings which are also part of KBK’s contact rate performance measure. As a result, our contact rates may severely underestimate the extent to which some puskesmas manage to approach the target contact rates.

Secondly, it would have been preferable to use puskesmas level data rather than average district level data, but these were not publicly available. Nevertheless, district-level analysis in primary care is of value because the implementation of KBK itself was rolled out at the district level. Since each district local government has the authority to allocate the health budget and decide on the proportion of capitation in its puskesmas (BPJS Kesehatan, 2015a), district policy can influence KBK impact.

Finally, the intervention also aimed to increase accountability of puskesmas, strengthen local governance, reduce waiting times and increase quality. Our data did not allow an assessment of the effects of the program on these additional outcomes.

4.6. Conclusion and policy recommendations

We estimated the impact of the introduction of Indonesia's performance-based capitation scheme KBK. Using a difference-in-differences approach we find a small increase in primary care visits but the overall effects of the program were far below the targets initially set. The program increased the contact percentage by 0.578 per 100, and the chronic disease contact percentage by 1.15 per 100. KBK did not significantly improve the non-specialistic referral rate in the treated districts.

We recommend the Indonesian government to initially lower the targets and subsequently increase these step by step on an annual basis. According to the Ministry of Health, only 2,962 puskesmas (out of 9,767 puskesmas i.e. 30%) are able to provide health care services according to a set minimum standard (Ministry of Health, 2017) and it might also be very hard for these facilities to reach the set utilization targets. Setting moderate goals will likely produce better results than setting targets that are beyond reach (Locke and Latham, 2002).

Setting the same targets for all puskesmas may have discouraged some to act if these targets were out of reach, while for relatively well-endowed facilities less effort is required to meet the KBK targets. A target based on previous achievements or of that of a group of puskesmas with a similar achievement level might provide a greater incentive to change provider behaviour. While a gradual approach, also based on past performance, may prove to be more effective than enforcing a uniform performance threshold, the goal should remain to move towards universal health coverage as the program is rolled out nationwide.

5

CHAPTER 5

When the smoke gets in your lungs: short-term effects of Indonesia's 2015 forest fires on health care use

With Menno Pradhan, Robert Sparrow and Eddy Van Doorslaer

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Abstract

Background:

The forest fires that ravaged parts of Indonesia in 2015 were the most severely polluting of this century but little is known about their effects on health care utilization of the affected population. We estimate their short-term impact on visit rates to primary and hospital care with particular focus on visits for specific smoke-related conditions (respiratory disease, acute respiratory tract infection (ARTI) and common cold).

Method:

We estimate the short-term impact of the 2015 forest fire on visit rates to primary and hospital care by combining satellite data on Aerosol Optical Depth (AOD) with administrative records from Indonesian National Health Insurance Agency (BPJS Kesehatan) from January 2015-April 2016. The 16 months of panel data cover 203 districts in the islands of Sumatra and Kalimantan before, during and after the forest fires. We use the (more efficient) ANCOVA version adaptation of a fixed effects model to compare the trends in healthcare use of affected districts (with AOD value above 0.75) with control districts (AOD value below 0.75). Considering the higher vulnerability of children's lungs, we do this separately for children under 5 and the rest of the population adults (>5), and for both urban and rural areas, and for both the period during and after the forest fires.

Results:

We find little effects for adults. For young children we estimate positive effects for care related to respiratory problems in primary health care facilities in urban areas. Hospital care visits in general, on the other hand, are negatively affected in rural areas. We argue that these patterns arise because accessibility of care during fires is more restricted for rural than for urban areas.

Conclusion:

The severity of the fires and the absence of positive impact on health care utilization for adults and children in rural areas indicate large missed opportunities for receiving necessary care. This is particularly worrisome for children, whose lungs are most vulnerable to the effects. Our findings underscore the need to ensure ongoing access to medical services during forest fires and emphasize the necessity of catching up with essential care for children after the fires, particularly in rural areas.

5.1. Introduction

The forest fires that affected two islands in Indonesia in 2015, between June and October, were the most severe and polluting of this century, producing more CO_2 emissions than the average daily greenhouse gas emissions in the entire US economy (Field et al., 2016; Harris et al., 2015). The fires burned around 2.6 million hectares of land, estimated at four and half times the size of Bali (World Bank, 2016). As a result of this, with around 96.937 active fires detected, global emissions in Indonesia skyrocketed with approximately 1,043 million tons of CO_2. During the peak months of Sept-Oct, the $C0_2$ emissions exceeded that of the entire European Union (Huijnen et al., 2016) and endangered the life and health conditions of the Indonesian population. This research estimates the impact of the 2015 fires on health care utilization in primary care facilities and hospitals that participate in the national health insurance scheme. The aim is to investigate to what extent the health system was able to provide the medical respiratory care that is required to mitigate any potential negative health impacts.

Forest fires can have severe long lasting impacts on human health. For Indonesia, these have been studied extensively for the 1997 forest fires, which were even larger than those in 2015, emitting about four times as much $C0_2$ (Huijnen et al., 2016). The population census of 2000 recorded 15,600 fewer children than expected in the birth cohort of the affected areas, which (Jayachandran, 2009) was attributed mostly to early childhood mortality. Children that did survive also had lower human development outcomes. They were found to grow shorter in height (Tan-Soo & Pattanayak, 2019), to have lower lung capacity (Rosales-Rueda & Triyana, 2019) and to score six percent lower on cognitive tests by age 8 (Shrestha, 2019). Adults exposed to the fires were less able to perform daily activities in the year of the forest fire (Frankenberg et al., 2005).

Appropriate and prompt treatment is crucial to reduce morbidity from wildfire smoke exposure (CDC Health Alert Network, 2023). Children, because they inhale more smoke relative to their body weight and because their functions are still developing, and those with pre-existing respiratory conditions are particularly vulnerable. Most of the evidence on health care utilization in response to forest fires stems from developed countries. In Singapore, for instance, Sheldon and Sankaran (2017) found that the Indonesian haze in 2013-2015 increased polyclinic attendances for acute respiratory tract infections and acute conjunctivitis. These visits were linked to the deterioration in air quality during the haze. For Australia, which is also prone to frequent forest fires, Chen et al. (2006) reported that bushfire smoke in Brisbane was significantly linked to increased hospital visits for respiratory illness. In America the forest fires in Hoopa Valley, California, caused a particulate matter that led to increasing asthma, coronary artery disease and headache visits of Hoopa and nearby communities (Lee et al., 2009). Similar studies in low- and middle income countries are far fewer because air quality stations in forests or land are scarce, and not easily related to reliable administrative data on health records. This study intends to contribute to filling this gap.

For Indonesia, the literature on the health effects of forest fires is relatively small. Arifin and Setyawan (2022) compared the health of people living in municipalities with and without the presence of a palm oil company in 2014. Palm oil companies use forest fires to clear land, and they find that communities that host them more often experience forest fires and have worse health outcomes. Our study contributes to this study by focusing on particularly severe forest fire, and we compare control and treatment groups based on the AOD level (related to smoke), rather than the presence of a palm oil plantation. In spite of differences, Arifin and Setyawan (2022) do report similar results regarding the impact of forest fires on children's health (increasing the probability of asthma in children) and on hospitalizations of children (and elderly) for respiratory reasons. Moreover, our study exploits information on healthcare visits for smoke-related diseases on a much more frequent, i.e. monthly basis, which is not provided in the other studies.

Further, Jayachandran (2009) investigated the impact of the Indonesian 1997 forest fire on fetal infant and child mortality. She analyzed combined data of particulate measures (UV Aerosol Index) and Indonesian 20000 census data, and found that the probability of children surviving declined if they resided in a forest fire location during a forest fire time. Our study add to this literature on the relationship between healthcare visits and smoke-related diseases, even though in a different episode (2015 forest fire). Unlike Jayachandran and Arifin, who employed cross-sectional data, we use longitudinal district level data, collected on a monthly basis, and also captured effects after the forest fire period ended.

To investigate whether the effects of forest fire are the result of changes in the need for health care or the accessibility of health care, we estimate impacts both for general outpatient care and for care specifically related to respiratory problems. We would expect the latter to respond most to need effects. We combine data on Aerosol Optical Depth (AOD) obtained from satellite data with administrative data from the National Health Insurance (JKN) members' utilization of outpatient services in primary health facilities and hospitals, in districts affected by the fires and in a selected set of control districts. The detailed diagnosis codes included in the JKN data allow us to focus our analysis on treatment for respiratory conditions and do a separate analysis for children below five. We consider both the period of the forest fires, and the six months succeeding the forest fires. While in the latter period the smoke had disappeared, residents may still need care because they could not access it during the fires, or because their health condition has not yet improved. We apply an ANCOVA estimation framework that corrects for outcomes observed in the pre-forest fire period.

The remainder of the paper is structured as follows. Section 5.2 discusses how forest fires could affect health and the required health care responses. Section 5.3 describes the construction of the analysis dataset, section 5.4 the estimation method and section 5.5 presents the results. We discuss the implications of the results in section 5.6. Finally, section 5.7 presents the conclusions of this research.

5.2. Forest fire smoke, health, and healthcare use

Forest fire smoke produces a complex mixture of gases, particles, water vapor, organic debris, and minerals due to incomplete combustion. Its characteristics depend on a number of variables, including the kind and amount of materials (wood and plants) that is burned, the temperatures that the fires produce, as well as the wind and weather conditions more generally (Indonesian Pulmonologist Association (PDPI), 2019). Smoke from forest fires typically contains three components: (a) gases like, for example, sulphur dioxide (SO_2), nitrogen oxides (Nox), carbon monoxide (CO), carbon dioxide (CO_2), and others. (b) Particulate matter (PM) describes the particles deriving from forest fires classified by their size. Particles sizes larger than 10 micrometers can irritate the eyes, nose, and throat but typically do not penetrate the lungs. Smaller particles can be inhaled into the lungs. Sizes between 2.5 and 10 micrometers are classified as coarse particles (PM10), while sizes of 0.1 to 2.5 micrometers are considered fine particles (PM2.5). (c) Other materials in a somewhat larger quantity, such as metal, dioxin, benzene, toluene, and polycyclic aromatic hydrocarbon (PAH) (Indonesian Pulmonologist Association (PDPI), 2019).

The primary contaminant is particulate matter (PM) and its effects on human health depend on particle size. PM10 enters through the throat and nose and deposits in the heart and surface of the lungs. This PM10 deposit can cause inflammation and tissue damage (California Air Resources Board, 2023). Further, PM 2.5 can enter the deeper part of the lungs and even can go to bloodstream. Population groups which are more sensitive to smoke from forest fires include: seniors, expectant mothers, children, people who have had heart or lung disease in the past (such as those who have asthma, chronic obstructive pulmonary disease, or COPD), and those who are pregnant. People with other chronic illnesses may also be at greater risk (Indonesian Pulmonologist Association (PDPI), 2019).

5.3. Data

BPJS Kesehatan has provided us with monthly district aggregated data of selected ICD10 (WHO, 2010b) coded utilization from all JKN members for the purpose of this study. The mean JKN coverage in our district sample is 57%, with 64.08% in city/urban and 52.30% in regency/rural. While JKN coverage is far from complete, we believe that it nonetheless provides a good impression of the utilization responses in the area. We expect that JKN members are more likely to use the care in response to the forest fires as compared to non JKN members. If this is the case, then our estimates are an upper bound of the demand response. Data on fire and air quality were obtained from the MODIS satellite scan. We get shapefile data from the Global Administrative Areas (GADM) database that provides us with a statistical geolocation code (GADM, 2020) that enables us to merge air pollution data and healthcare utilization at the district level (see Figure 1).

Healthcare utilization data

Our dependent variables are the monthly district-level aggregates of all outpatients' visits and outpatient visits for smoke related diseases (respiratory illness, common cold and ARTI) of JKN members to primary care and hospitals. The healthcare utilization data are monthly observations from January 2015 to April 2016 (16 months) for 203 districts located in Sumatra and Kalimantan Islands for 4 aggregates: (i) total outpatient visits, (ii) all type of respiratory disease (ICD10: J00-J22), and the two most common diagnoses related to forest fire smoke namely (iii) Common Cold (Nasopharyngitis) (ICD10: J00) and (iv) Acute Respiratory Tract Infection (ARTI) (ICD10: J069) (BPJS Kesehatan, 2016a). The typical symptoms of common cold such as sneezing, nasal congestion, and excess mucus production (Pittara, 2022) are also present during smoke related respiratory problems. Meanwhile, ARTI common signs are fever, cough, cold, out of breath, weight loss and myalgia (Maharani, 2019). Because the symptoms for these two diseases tend to occur in the first two weeks after the first contamination these types of utilization are suitable to evaluate short term effects of smoke inhalation.

We obtain visit rates per 1,000 JKN members for each type of utilization by dividing monthly district visits by the number of JKN members in a district (in the respective age group) and multiply by 1,000. We use the number of JKN members on January 2015 as the denominator for all periods to avoid problems with endogenous changes in enrolment in JKN. We construct separate utilization rates for those under five years old and those five years and older, and for rural (Kabupaten) and urban (Kota) districts.

Air Pollution data

Aerosol Optical Depth (AOD)

We use Aerosol Optical Depth (AOD) from satellite imagery as our main measure of smoke pollution following approach from (Hein et al., 2022). AOD is closely linked to Particulate Matter 2.5 (PM 2.5) (Sorek-Hamer et al., 2016) which can be detrimental to human health if its value exceeds a critical level (WHO, 2021). Aerosol optical depth (AOD) is determined by airborne particles like dust, smoke, and pollution that may obstruct sunlight by either absorbing it or dispersing it. It indicates the amount of direct sunlight that is blocked from reaching the ground by these aerosol particles. One main advantage of AOD is that global coverage is possible by computing spatial averages over the user-selected areas (districts in our case) over a given time period in Google Earth Engine system (GEE) (Gorelick et al., 2017). A higher value of AOD generally indicates a higher share of aerosols like smoke and dust in the atmosphere.

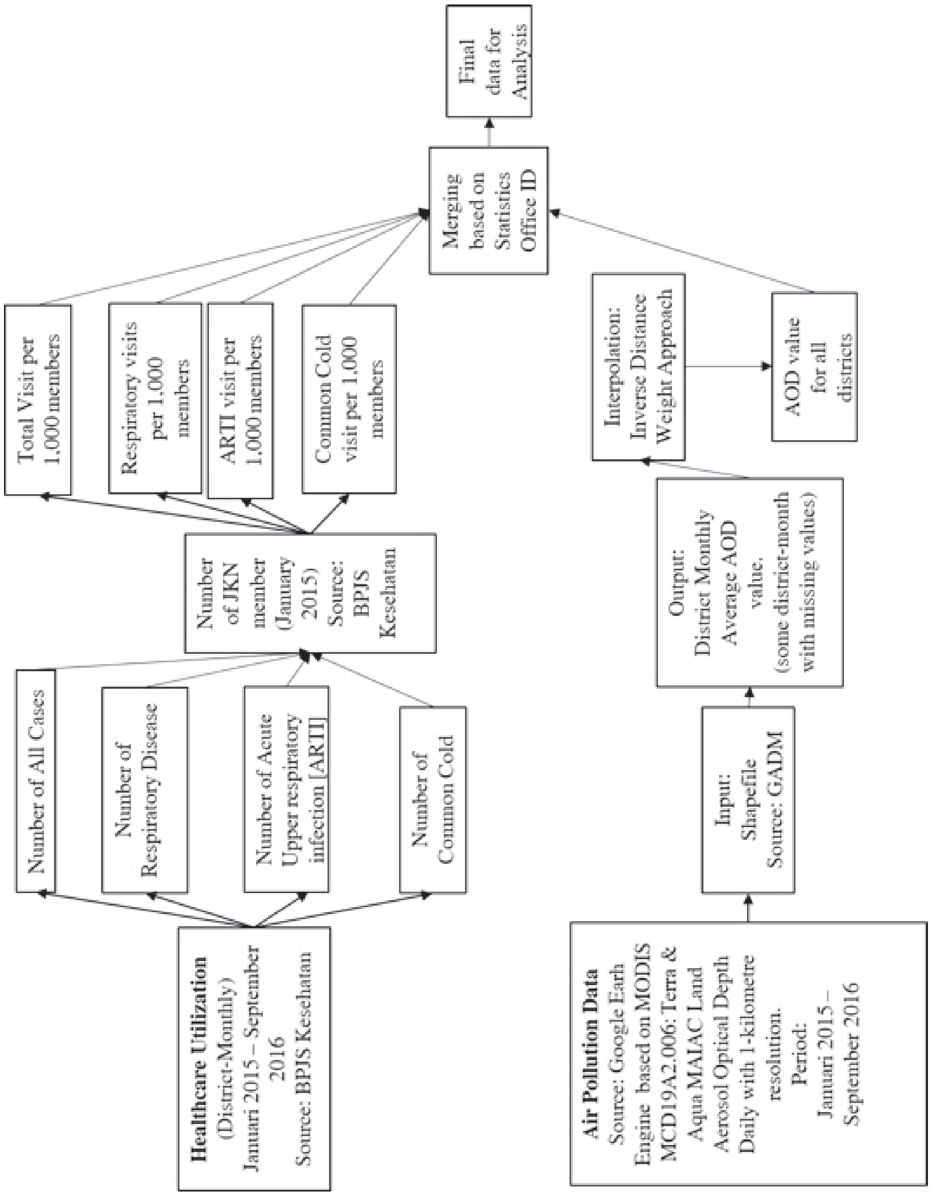
For Indonesia, an AOD value above 0.75 represents a high concentration of aerosols in the atmosphere from biomass burning (Banerjee et al., 2021). Most studies that look at impacts of smoke in developed countries used PM2.5 as a measure of air pollution, which is measured through ground stations. Because this information is not widely available for Indonesia, we use the AOD measure instead. The global maximum AOD that is reported by MODIS sensors is 5 and most of the distribution of AOD values are between 0 and 0.5.

The Google Earth Engine (GEE) database that we use is widely used for public health-environment research[6]. It contains atmospheric data from various satellites. We use MODIS MCD19A2.006: Terra & Aqua MAIAC Land Aerosol Optical Depth Daily with 1-kilometre resolution data within GEE database. GEE produces the AOD value of the district shapefile that

[6] GEE is geospatial analysis software that collect and examine satellite photos of our world. We can access this database through the link https://earthengine.google.com/. Scientists and non-profits use Earth Engine for remote sensing research, predicting disease outbreaks, natural resource management, and more. We use user-friendly data environment through https://code.earthengine.google.com/.

we input into the GEE by taking the monthly average of daily data. The district-monthly AOD can then be merged with the district-monthly healthcare utilization using Indonesian Statistics Office (Badan Pusat Statistik) geolocation identification. In case clouds are covering the land when the satellite is crossing, there are missing values that do not contribute to the spatial averages. In such cases we use geospatial interpolation, the details of calculation and assessment of interpolation accuracy are explained in Appendix D1.

Figure 1. Flowchart of data construction for analysis



5.4. Methods

This study is quantitative research with causal design using longitudinal data. We use data from three different sources. We link primary care and hospital admission data from the Indonesian National Health Insurance Agency (JKN) with geospatial location and air quality data. We define districts as being affected by the forest fire if the AOD level during the 5-month (June-October 2015) period of the forest fire exceeds 0.75, which is a locally validated threshold for unhealthy AOD values (Banerjee et al., 2021). Appendix Figure 1 presents the average AOD levels in treatment and control district by month. AOD levels peaked in October 2015 at 2.55 in treatment districts.

Our estimation model is based on the general idea that healthcare utilization is a function of our air quality indicator (AOD). We estimate this function separately for children under 5 (because children's lungs are more vulnerable) and the rest of the population (> 5), for both urban and rural locations. Because Appendix Figure 1 shows that there is a clear spike in AOD values during the forest fire period June-October 2015, we use an ANCOVA specification of the regression model to account differences between affected and non-affected districts before the forest fire period, by including pre-fire outcome $H_{k,0}$ (averaged over January-May 2015) as control variable. The main advantage of ANCOVA over a conventional difference-in-difference (DID) specification is gains in efficiency resulting in lower estimated standard errors (McKenzie, 2012). In terms of identification of causal effects, both methods (DID and ANCOVA) rely on the parallel trend assumption that, in the absence of the forest fires and elevated AOD levels, the trends in health care utilization would have been the same in affected and non-affected districts.

The variable $Affected_k$ equals 1 if a district k experiences an average AOD of more than 0.75 during forest fire period June-October 2015. The dummy variable $During\ fire_t$ equals 1 for the months of the forest fire, and the variable $After\ fire_t$ equals one for the six months after the forest fire, November 2015 – April 2016. Our estimates of interest are the coefficients for the interaction terms of $Affected_k$ with the two different periods: σ_1 captures the impact of fire induced air pollution during the forest fire period, while σ_2 capture delayed effects that occurred after the period of fire. We also include time dummies α_t. This yields the following ANCOVA specification:

$$H_{k,t} = \sigma_0 + \sigma_1 During\ fire_t * Affected_k + \sigma_2 After\ fire_t * Affected_k + \sigma_3 H_{k,0} + \alpha_t + \varepsilon_{kt} \qquad (2)$$

We also provide standard difference-in-difference (DID) estimates as a robustness test to the ANCOVA results. We expect the DID results to show higher standard errors compared to the ANCOVA.

5.5. Results

Descriptive Statistics

Table 1 shows summary statistics of our sample pre-fire, during fire and after fire. We find that all age primary care use in affected districts for total, respiratory disease and common cold is lower than in control districts in pre-fire, during and after fire period (but only for common cold it is statistically significant). In contrast, the visit rate for all outcomes of under five years old are higher but these differences are not statistically significant. For hospital care we see an opposite pattern, with higher utilization in non-affected districts in all time periods. The mean AOD value is about the same during the pre-fire period, with mean AOD of 0.30 and 0.28 for the affected and control districts, respectively. During the forest fire period, the mean AOD levels jump sharply for affected districts to 1.12, and slightly for control districts to 0.52. After the fires, the air quality returns back to pre-fire levels.

Figure 2 maps the AOD maximum values before, during and post forest fires. The AOD values are normally below 0.75 represented by light yellow for all districts in Sumatera and Kalimantan in before and after forest fire period. This is in line with a similar spike in the national AOD levels for the same period observed by (Eko Cahyono et al., 2022).

Figures 3 and 4 show trends of primary care and hospital care use in affected and control districts, for (A) under five years old and (B) over five years old. In Figure 3A, we see an increase during and after the forest fires for total visits, respiratory disease and common cold visits in a primary care facility for under five years old in affected districts. Control districts also experience an increase in outpatient care, but not as strong as in affected districts. For those age five years and older, we observe some increase in utilization but no difference in trends between affected and control districts. Figure 4A and 4B show that affected districts have relatively lower hospital outpatient visit rates, but the trends are fairly similar to those for the control districts, with a dip in visits for respiratory disease during the forest fire period.

To further assess the parallel trends assumption, we compare the monthly changes in the outcome variables in the pre-fire period, by interacting month dummies variables with the variable indicating affected status. We find that none of the coefficients for the interactions are statistically significant (Table D9 and Table D10). We also perform a joint significance test of the interaction terms of time trend and forest fire affected status using the joint F-test, which never rejects the null hypothesis that the pre-fire time trends are significantly different in to be treated and controls (Table D11). This leads us to conclude that while there are some initial differences in outcomes between the affected and control group, the trends for these groups are similar before the forest fires occurred. We believe that this builds some confidence in the parallel trends assumption for the period after June 2015.

Estimation Results

Our main ANCOVA estimation results are presented in Table 2 for outpatient care in primary care facilities and in Table 3 for hospitals. The forest fires are estimated to have caused an immediate increased utilization of primary care in affected districts by 1.42 visits (but not statistically significant), and a delayed increase of 3.13 visits after the fire period, per 1,000 under five enrollees for total primary care visit. This means a 17% increase of total primary visits after forest fire compared to pre-fire utilization levels.[7] When we look at the causes for the outpatient visits, we find statistically significant effects after the forest fire period for respiratory disease (2,41 visits per 1,000) and common cold (2.14), which translates to increases of respectively 22% and 43%.

However, we find opposite results for utilization at hospital for under-fives, with visit rates decreasing by 3.26 during the fires and 5.15 afterwards (Table 3), which constitutes a 10% and 16% drop relative to observed pre-fire utilization levels in the affected districts. For the population over five years old there appears to have been no discernable impacts of forest fire on health care use.

Our geographic breakdown shows that the impact of the fires on primary healthcare use is mainly due to utilization changes in urban rather than in rural areas. For example, we find consistent positive effects of forest fire on overall utilization, respiratory disease and common cold for under-fives (Table 4). However, for hospital care we observe negative effects for both urban and rural districts, although the estimates for urban districts are less precise (Table 5).

[7] The DID estimates in Appendix Table D1-D2 show similar results, albeit larger point estimates.

Table 1. Distribution of healthcare utilization share across socioeconomic quintiles (2015-2017)

	Hospital Inpatient				Hospital Outpatient				Primary Care Outpatient			
	Contact per 100 individuals in one year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)	Contact per 100 individuals in one year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)	Contact per 100 individuals in one year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)
	1	2	3	4	5	6	7	8	9	10	11	12
2015												
Poorest	1.57	11.06	236.60	9.77	11.81	9.14	14.15	8.09	169.53	19.14	3.27	17.81
2nd quintile	1.94	13.44	243.00	12.23	15.74	12.32	14.76	11.46	181.69	20.53	3.44	19.80
3rd quintile	2.55	17.49	250.07	16.55	20.88	15.91	15.01	14.93	184.09	20.98	3.53	20.87
4th quintile	3.42	23.08	261.95	23.03	31.02	23.01	15.74	23.01	182.66	20.80	3.65	21.39
Richest	5.10	34.92	276.70	38.42	52.34	39.62	16.75	42.50	160.16	18.55	3.85	20.14
Mean	2.79	100	248.99	100.00	24.92	100	15.04	100.00	175.99	100	3.45	100.00
2016												
Poorest	1.52	10.31	223.54	9.24	12.17	9.46	14.02	8.42	156.30	18.92	3.46	17.60
2nd quintile	2.03	13.87	232.14	13.03	16.47	12.79	14.85	12.02	170.96	20.79	3.56	20.08
3rd quintile	2.52	17.29	233.66	16.32	20.13	15.72	14.98	15.13	171.26	20.77	3.67	20.47
4th quintile	3.56	24.41	243.49	24.29	28.86	22.70	15.25	22.41	175.59	21.27	3.76	21.82
Richest	4.98	34.12	256.08	37.12	50.31	39.33	16.09	42.01	150.72	18.26	4.03	20.02
Mean	2.93	100	235.13	100.00	25.64	100	14.91	100.00	164.89	100	3.60	100.00
2017												
Poorest	1.72	10.81	222.76	9.58	9.58	9.16	15.17	8.45	130.09	19.06	3.89	17.41
2nd quintile	2.34	14.70	234.03	13.84	13.48	12.76	15.45	12.16	138.32	20.08	4.01	19.10
3rd quintile	2.76	17.57	237.93	16.77	16.33	15.60	15.63	15.00	142.31	20.80	4.14	20.68
4th quintile	3.59	23.23	240.19	22.86	22.38	21.94	15.92	21.62	146.00	21.44	4.26	21.97
Richest	5.41	33.69	248.28	36.95	42.45	40.54	16.25	42.77	131.47	18.62	4.22	20.85
Mean	3.28	100	236.75	100.00	21.90	100	15.68	100.00	137.74	100	4.08	100.00

Source: Authors' calculation based on BPJS-*Kesehatan* claims data and SUSENAS 2015-2017. Note: Distribution of socioeconomic quintiles is based on per capita expenditure of each year (regional CPI adjusted).

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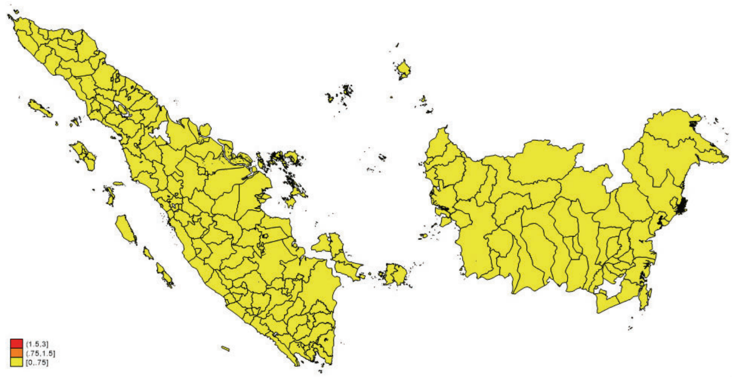
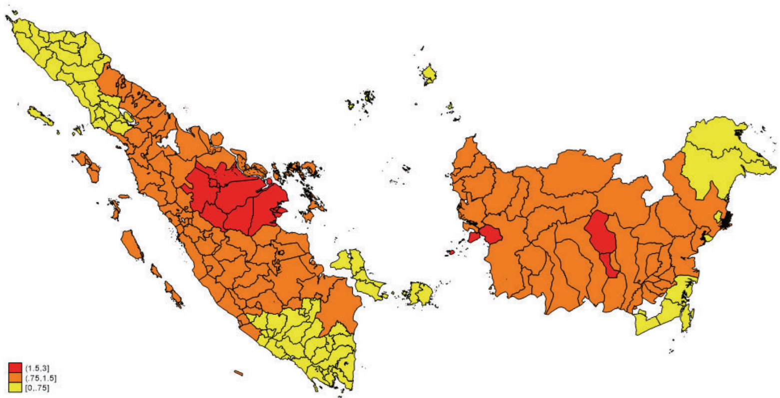
Figure 2. Maximum AOD Level before, during and after forest fire period in Sumatera and Kalimantan

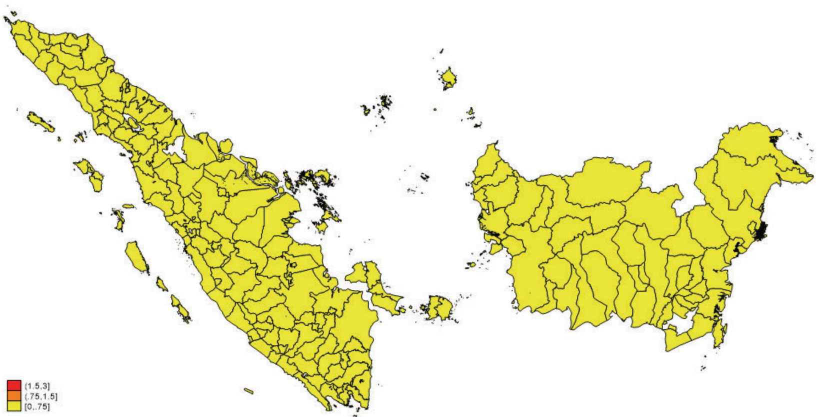
Before Forest Fire



During Forest Fire



After Forest Fire

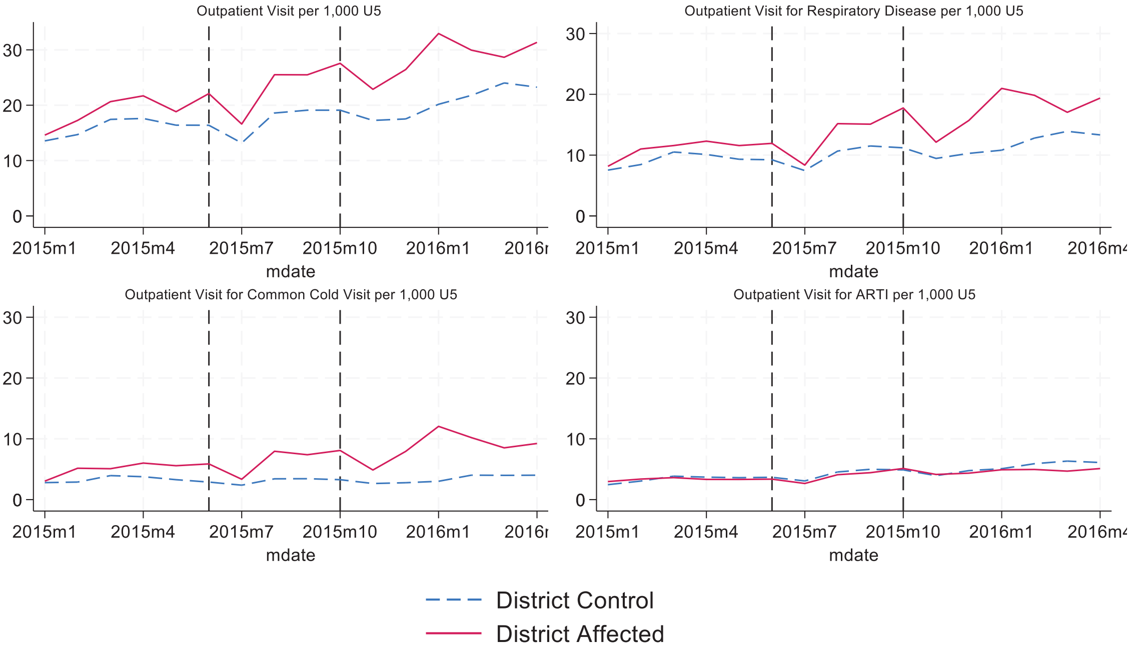


Source: Aerosol Optical Depth derived from MODIS satellite data.

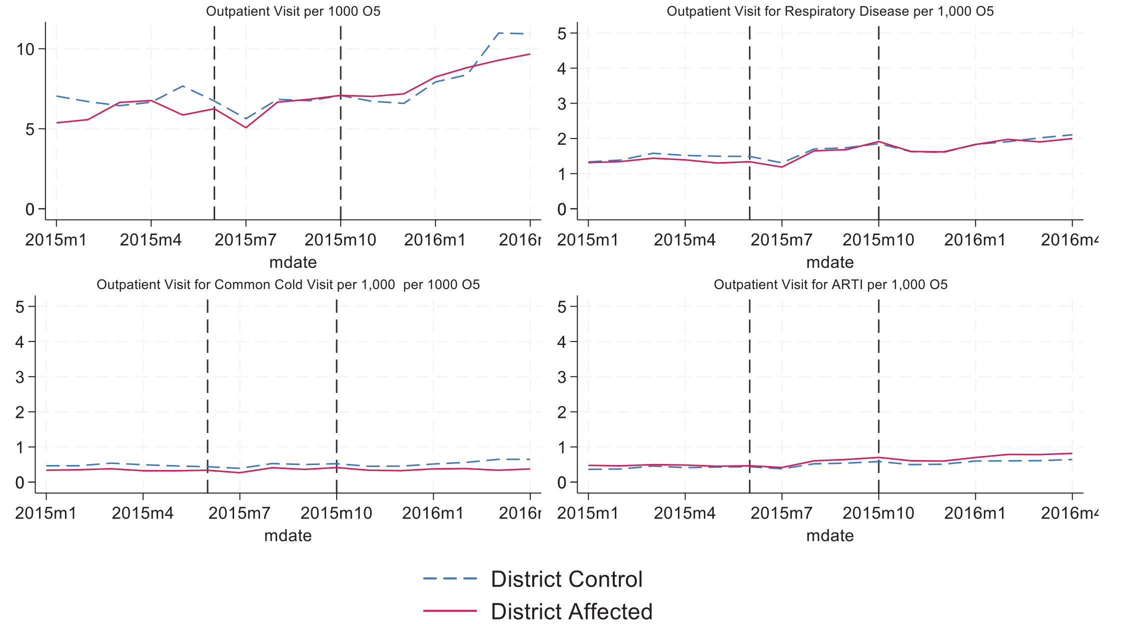
Note: Pre-Fire (January-May 2015); During Fire (June-October 2015); After Fire (November 2015 – April 2016).

Figure 3. Primary care outpatient and respiratory disease trend in Sumatera and Kalimantan Islands (Monthly visit per 1,000 age group enrollees, 2015-2016)

(A) Under five years old



(B) Over five years old



Source: Author analysis based on BPJS Kesehatan data

Note: District affected is a district with average monthly AOD value more than 0.75 during Forest Fire Period (June to October 2015).

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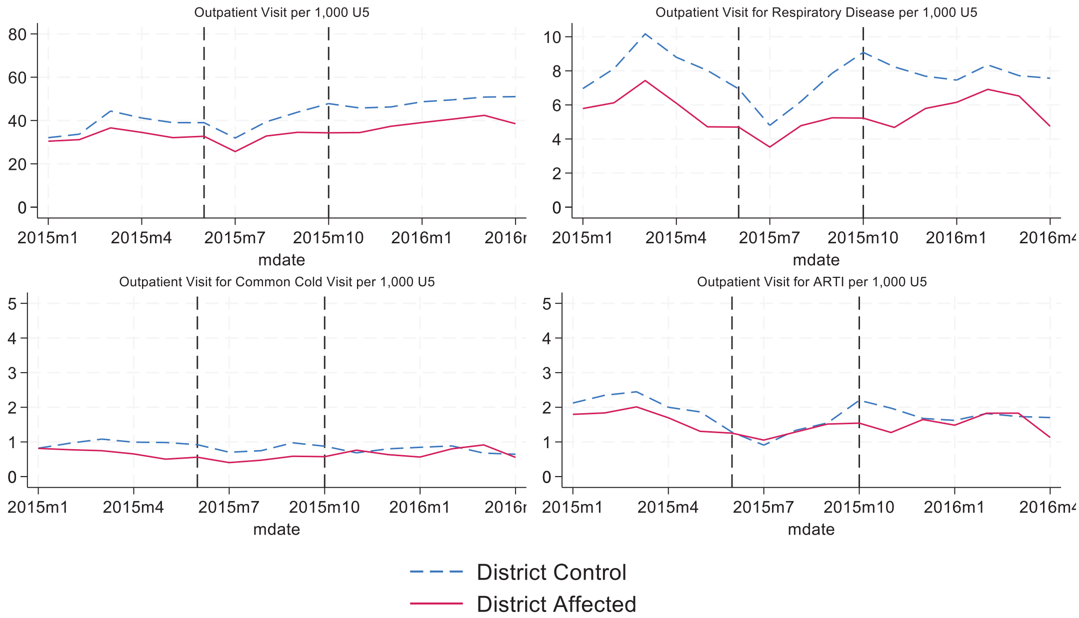
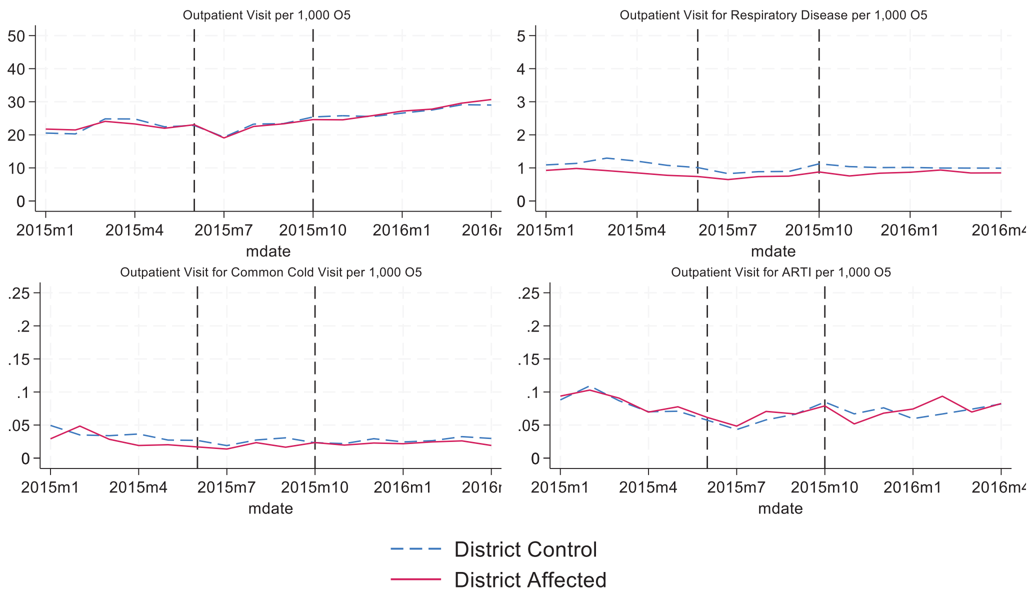
Figure 4. Hospital care outpatient and respiratory disease trend in Sumatera and Kalimantan Islands (Monthly visit per 1,000 age group enrollees, 2015-2016)

(A) Under five years old



(B) Over five years old



Source: Author analysis based on BPJS Kesehatan data
Note: District affected is a district with average monthly AOD value more than 0.75 during Forest Fire Period (June to October 2015).

Table 2. The Effect of Forest Fire Affected Districts on Primary Care Utilization 2015-2016 - ANCOVA

	Under Five Years Old				Over Five Years Old			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Visit per 1,000 Under Five members	Respiratory visits per 1,000 Under Five members	Common Cold visit per 1,000 Under Five members	ARTI visit per 1,000 Under Five members	Total Visit per 1,000 Over Five members	Respiratory visits per 1,000 Over Five members	Common Cold visit per 1,000 Over Five members	ARTI visit per 1,000 Over Five members
During Forest Fire	1.421	0.432	0.264	-0.277	0.160	0.0312	-0.0135	0.00239
	(1.408)	(1.089)	(0.791)	(0.269)	(0.259)	(0.0606)	(0.0258)	(0.0295)
After Forest Fire	3.130*	2.406*	2.136***	-0.655	0.312	0.0679	-0.0845***	0.0661
	(1.634)	(1.251)	(0.801)	(0.406)	(0.347)	(0.0822)	(0.0290)	(0.0447)
Pre-Fire Outcome	1.743***	1.847***	1.920***	1.120***	1.032***	0.957***	0.751***	1.053***
(January-May 2015)								
	(0.137)	(0.217)	(0.234)	(0.0328)	(0.0703)	(0.0249)	(0.0254)	(0.0325)
Constant	-11.74***	-8.349***	-3.808***	-0.0807	-0.477	0.0336	0.0828***	-0.0193
	(2.765)	(2.404)	(1.353)	(0.276)	(0.483)	(0.0711)	(0.0310)	(0.0307)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	2,203	2,203	2,203	2,203	2,203	2,203	2,203	2,203

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

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Table 3. The Effect of Forest Fire Affected Districts on Hospital Utilization 2015-2016 - ANCOVA

	Under Five Years Old				Over Five Years Old			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Visit per 1,000 Under Five members	Respiratory visits per 1,000 Under Five members	Common Cold visit per 1,000 Under Five members	ARTI visit per 1,000 Under Five members	Total Visit per 1,000 Over Five members	Respiratory visits per 1,000 Over Five members	Common Cold visit per 1,000 Over Five members	ARTI visit per 1,000 Over Five members
During Forest Fire	-3.261***	-0.275	-0.132	0.170	-0.200	0.00542	-0.00289	0.00213
	(0.951)	(0.318)	(0.0812)	(0.105)	(0.396)	(0.0343)	(0.00301)	(0.00555)
After Forest Fire	-5.147***	-0.0767	0.141*	0.0606	0.235	0.0377	-0.00145	0.000518
	(1.244)	(0.298)	(0.0791)	(0.127)	(0.454)	(0.0394)	(0.00257)	(0.00630)
Pre-Fire Outcome	0.979***	0.829***	0.704***	0.670***	1.032***	0.737***	0.495***	0.853***
(January-May 2015)								
	(0.0149)	(0.0306)	(0.0423)	(0.0383)	(0.0125)	(0.0253)	(0.0579)	(0.108)
Constant	2.831***	-0.0410	0.215**	-0.113	-0.222	0.108***	0.00675*	-0.0152
	(1.030)	(0.333)	(0.0915)	(0.117)	(0.466)	(0.0412)	(0.00350)	(0.0114)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	2,203	2,203	2,203	2,203	2,203	2,203	2,203	2,203

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

Table 4. The Effect of forest fire affected districts on primary care utilization 2015-2016 under five years old (urban v– rural) - ANCOVA

	City + Regency				City (urban)				Regency (rural)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members
During Forest Fire	1.421	0.432	0.264	-0.277	5.798***	3.283***	1.405***	0.252	0.128	-0.619	-0.648	-0.345
	(1.408)	(1.089)	(0.791)	(0.269)	(1.410)	(1.026)	(0.448)	(0.651)	(1.550)	(1.198)	(0.946)	(0.287)
After Forest Fire	3.130*	2.406*	2.136***	-0.655	5.924***	2.910**	0.748	-0.242	2.347	2.035	1.926**	-0.695
	(1.634)	(1.251)	(0.801)	(0.406)	(1.939)	(1.326)	(0.532)	(0.796)	(1.697)	(1.258)	(0.892)	(0.466)
Pre-Fire Outcome	1.743***	1.847***	1.920***	1.120***	0.997***	0.938***	0.610***	1.114***	1.855***	1.995***	1.941***	1.193***
(January-May 2015)												
	(0.137)	(0.217)	(0.234)	(0.0328)	(0.0328)	(0.0407)	(0.0526)	(0.0447)	(0.147)	(0.242)	(0.237)	(0.0475)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	2,203	2,203	2,203	2,203	451	451	451	451	1,752	1,752	1,752	1,752

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

Table 5. The Effect of forest fire affected districts on hospital care utilization under five years old (urban v– rural) - ANCOVA

	City + Regency				City (urban)				Regency (rural)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members
During Forest Fire	-3.261***	-0.275	-0.132	0.170	-2.870	-0.235	0.131	0.0956	-3.493***	-0.338	-0.198**	0.182
	(0.951)	(0.318)	(0.0812)	(0.105)	(2.806)	(0.605)	(0.157)	(0.181)	(0.956)	(0.365)	(0.0927)	(0.122)
After Forest Fire	-5.147***	-0.0767	0.141*	0.0606	-6.362	-2.415***	-0.152	-0.732***	-5.415***	0.407	0.207**	0.238
	(1.244)	(0.298)	(0.0791)	(0.127)	(4.457)	(0.682)	(0.150)	(0.260)	(1.103)	(0.330)	(0.0918)	(0.145)
Pre-Fire Outcome (January-May 2015)	0.979***	0.829***	0.704***	0.670***	0.914***	0.681***	0.649***	0.692***	0.959***	0.847***	0.708***	0.663***
	(0.0149)	(0.0306)	(0.0423)	(0.0383)	(0.0231)	(0.0388)	(0.0896)	(0.0493)	(0.0195)	(0.0353)	(0.0438)	(0.0444)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	2,203	2,203	2,203	2,203	451	451	451	451	1,752	1,752	1,752	1,752

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

5.6. Discussion

Our analysis has led to at least five clear findings, all related to the four important distinctions that we make: respiratory versus other health care use, young (<5y) versus older (>5y) population, urban versus rural regions, and effects during versus after the forest fires.

First, perhaps the most important observation is that for the large majority of the 5+ population, *no effects* on respiratory or other health care utilization could be detected of the forest fires, neither in the short (5 months) period during, nor in the (6 months) period right after the forest fires: the fires do not seem to have caused the run on respiratory and/or other health care that one might expect given the reported longer term health outcomes. We find no short-term effects on either primary (clinic) or secondary (hospital) health care utilization of >5y olds, neither during nor after the fires. That may be surprising in view of the documented longer-term effects on health and raises questions about the ability of adequate (short term) health care use in preventing longer term health consequences on morbidity and mortality observed in Indonesia and elsewhere, but most of these reported effects were also for children (Jayachandran, 2009; Ye et al., 2021).

Secondly, we do find some positive health care utilization effects for under 5y olds, but they are opposite for primary care (which increases) and secondary care, (which decreases). The latter decrease is only observed for total hospital visits, not for respiratory disease specific visits. It raises questions about whether the fires may have had any indirect health impact through foregone other care use for children, i.e. for other than respiratory problems, as a result of reduced accessibility. Our data do not allow us to examine this possibility other than through a separate estimation for urban and rural parts of the country.

We use regency as a proxy of rural area and city for urban area. According to Kompas (2022) regencies typically encompass a larger area compared to cities, resulting in a higher number of disadvantaged villages within district boundaries. Moreover, regencies tend to have lower population densities compared to cities. In terms of livelihood, regency residents commonly engage in agriculture, while those in city are more involved in trade and services. In socio-cultural aspect, city residents often exhibit higher levels of education and better health outcomes compared to their counterparts in districts. Additionally, public service facilities (including education and health) are typically more developed in cities than in regencies. In the economic point of view, the average Gross Regional Domestic Product (GRDP) is lower in regencies than in cities.

This led to a *third* finding: the increase in primary care for young children is almost exclusively observed in the urban areas, not in the rural. It is only in urban clinics that we observe substantial increases both during and after the forest fires. This again points in the direction of only rural kids' primary care use not responding to the fire smoke exposure. Whether this is a consequence of a deliberate rural mother/parent choice not to seek care during/after the fires, or due to a more general disruption of primary care services in affected rural areas is something we cannot derive from our data.

The same urban-rural breakdown, but for children's hospital care use, led to a *fourth* finding: it revealed that almost the entire observed drop in total (i.e. non respiratory specific) visits is due to a reduction in *rural* hospital visits. Again, we argue that accessibility of hospitals during fires is much more restricted for rural than for urban mothers wanting to take their under 5s to the hospital for reasons unrelated to respiratory problems. If this is indeed the case, then it suggests that the health (care) burden deriving from smoke pollution is very unequally distributed, and far greater in rural than in urban areas.

Fifth and finally, the only instance where we see a clear difference in effects during versus after the fires is in common cold visits for children: again the significant rise in common cold visits *after* the fires is almost entirely due to a rise in rural clinic visits. This may be partly due to a catch-up effect for the significant drop that was observed *during* the fires. While it is surprising to see this for common cold visits and not for the more serious category of ARTI visits, we have to be aware that some of the visits labeled as common cold might simply be misclassifications or might sometimes develop into more serious conditions like ARTI later.

Our results contribute to the rather small literature on the health care utilization impacts of wildfire smoke, which has mostly focused on developed countries. Our results contrast to a similar study of Ye et al. (2021) which investigates hospital admissions resulting from wildfire smoke but for a much longer period (2000-2015) in Brazil. They find increased utilization of hospital services while our analysis indicates a decrease. A plausible explanation is that our study focuses on the much shorter intense period of forest fires which is likely to also have limited access through reduced mobility while the Brazil study has a much longer time frame. Ye et al. (2021) also find the strongest effects among children. Our findings also differ from those of Sheldon and Sankaran (2017) for Singapore, who found that an increase in pollution led to an increase in the frequency of weekly polyclinic visits for ARTIs while we do not find any increase in ARTI visits.

Our study is subject to various limitations. First, the AOD data per district are only a proxy measure for the PM2.5 concentrations which have been used in other health studies. Problems like cloud contamination, varied surface conditions, or flawed retrievals may result in inaccuracies or absence of the AOD values retrieved from the satellite (Handschuh et al., 2022). This may lead to a downward bias in our effect estimates. Second, our main outcome variable – health care visits – only relate to the JKN members in the two islands (Kalimantan and Sumatra). This is only 57% of the total Sumatera and Kalimantan resident population. Finally, the reasons indicated for the visits in the insurance administration (common cold, ARTI, other) may be subject to classification errors that could influence our findings.

5.7. Conclusion

This study aimed to estimate the short-term consequences of the forest fires that (two islands of) Indonesia endured from June to October 2015, for the use of health care at primary facilities and hospitals. We find that the health care utilization of the 5+ population was not affected but in the more urban places, parents did take their children to the primary care clinics in response to fire smoke and the observed drop in (both general and respiratory specific) hospital care use is generally not significant. We interpret this finding of forgone care as suggesting that the accessibility of care, whether perceived or real, was primarily restricted to rural areas, while it was less observed, if at all, during the fires in urban areas. It is quite possible that seeking care during times of fire and smoke is more hindered in rural than in urban communities. Foregone care is a situation where individuals either opt not to or are unable to access health services, even when they recognize a need for them (Kakietek, 2022). This raises equity issues as it would suggest that the effects of foregone care use are unequally distributed between urban and rural Indonesia. Our findings underline the importance of having available medical services in proximity during a period of forest fires, when transport and mobility is hindered by the same fires.

The reduced use of general hospital care for kids does, however, also raise important questions about the potential harmful effects of forgone care for other than respiratory reasons. Our analysis does not allow us to examine these longer-term health consequences, but if the foregone care use was essential, this is a possibility. The most important implication for health policy appears to be that in post-fire periods additional attention is needed for catching up with essential care for kids, especially in rural areas.

Indonesia has made commendable efforts to document and manage these natural disasters through agencies, such as the National Disaster Management Agency (BNPB) and the Ministry of Forestry and Environment. These organizations collect comprehensive data on the impact of disasters, encompassing affected regions, population demographics, and environmental conditions. However, this effort is fragmented and requires synchronisation in order to make these data more valuable for research. Thus, our present analysis is limited to the data that were available.

We recommend future synchronisation of healthcare data from BPJS Kesehatan and natural hazard data. As a result, researchers and policymakers could gain valuable insights into several critical areas. For instance, they could explore the effectiveness of healthcare responses during and after disasters, identify vulnerable populations, assess healthcare infrastructure readiness, and develop strategies to enhance healthcare preparedness in disaster-prone regions.

6

CHAPTER 6

Discussion

This dissertation investigates the transformation of health insurance coverage in Indonesia following the introduction of the National Health Insurance Program (JKN). It examines the impact of these changes on healthcare benefit distribution, payment systems, and preparedness for natural disasters. Our primary objective is to enrich the knowledge and understanding of the general populace and policymakers concerning evidence-based policy formulations that can be extrapolated from JKN experiences.

Policy recommendations based on the thesis findings.

Avoiding the adverse selection to ensure the long-term viability of the National Health Insurance Program (JKN)

Our study offers evidence with policy implications for the advancement of JKN coverage. Based on the findings from Chapter 2, we recommend that the Indonesian government focuses on maintaining JKN's financial sustainability by carefully managing the utilization of the self-enrolled health insurance (SEHI) scheme. We find the strongest correlation between the self-enrolled health insurance scheme and hospital utilization. Indonesian policymakers should interpret this finding with caution. It suggests a significant level of adverse selection. Creating voluntary health insurance enrolment is counterproductive for achieving Universal Health Coverage (UHC), as it disrupts essential risk pooling. A balanced contribution from individuals with varying health risks is crucial for maintaining sustainable coverage and preventing excessive premiums. This could have implications for the financial sustainability of JKN because this SEHI scheme has a low rate of active members but is used at a higher rate compared to other schemes (Trisnantoro, 2019). Additionally, mandatory health insurance (MHI) and health insurance for the poor (HIFP) both consistently show an increase in hospital inpatient care compared to the pre-JKN period. However, it still leans more towards the use of public facilities over private ones.

Expanding healthcare access in underprivileged regions

Our findings in Chapter 3 support the argument that geographical disparities continue to exist post-JKN due to a readiness gap in healthcare supply. In response, national and local governments should foresee making investments to enhance the quality of healthcare services and improve the accessibility of medical facilities and personnel in rural areas and districts outside of Java and Bali. One potential avenue to explore is to involve InaCBG (Indonesian DRG) pricing adjustment based on the healthcare supply readiness gaps by giving relatively more weight to less supplied regions. This approach has the potential to incentivize investments in health infrastructure in less supplied or remote regions of the existing gap between real cost and INA-CBG. The cost to build and operate a new facility in these regions is larger than in better-off regions. Thus, if potential revenue from JKN exceeds the cost, joining JKN is reasonable. Some hospitals complain that the INA-CBG tariff is lower than the real cost. This makes it less appealing to potential care providers (Handayani & Pratiwi, 2019). Further, INA-CBG adjustment by giving higher payments to the worse-off regions also ensures that the real cost is not paid by patients who still need to pay out-of-pocket payments (Cheng et al., 2022).

If the payment to provider is not adjusted by considering the geographical gap in healthcare supply, more healthcare provision tends to go to wealthier locations. In Chapter 3, we find a clear association between the average per capita household spending and hospital unit costs. This link is mainly driven by the relatively high healthcare expenses in Jakarta. In this city, the unit cost is 26.50 USD for a hospital outpatient visit, which is about 50% more than the national average of 17.50 USD. It is 530 USD for inpatient care, which is around 80% higher than the national average of 291.80 USD. These wide variations in regional hospital unit cost can be attributed to the presence of more advanced hospitals, such as Class A or B hospitals, or tertiary healthcare providers. Districts or cities with Class A (tertiary care) hospitals tend to receive greater JKN funding since they offer a more comprehensive range of high-quality medical services. It is important to note that these advanced hospitals are not evenly distributed across the country.

Taking into account district-specific unit price variations, the disparity in hospital benefit distribution intensifies. In 2017, the wealthiest group's share of benefits rose to 37% for inpatient care and 43% for outpatient care, while the shares for the poorest individuals declined to 10% and 8%, respectively. This trend is also reflected in primary care, where the wealthiest quintile contributed over 20%, compared to the poorest quintile's 17% in 2017. This towards wealthier groups can be attributed, in part, to JKN's gatekeeping mechanism, requiring referrals for reimbursement of higher-level care from community health centers. Variations in unit prices across districts favour wealthier individuals (who are most probably living closer to better supply of healthcare), as indicated by concentration curves consistently aligning with the diagonal line across all healthcare categories. This results in positively skewed concentration indices that are significantly higher for benefit distribution using district-specific unit cost, observed at the 1% level for all care categories.

Enhancing performance-based payment in healthcare services through better schemes and targeting

As Indonesia enforces Law Number 17 of 2023 on Healthcare (Government of Indonesia, 2023), performance-based financing becomes a pivotal element in healthcare program planning. This planning and budgeting initiative is known as *Rencana Induk Bidang Kesehatan* (RIBK) (Ministry of Health, 2023). This master plan will be a comprehensive guideline for local governments in the health sector's budgeting process. It shifts from mandatory spending shares (M. W. Kurniawan, 2023) with minimum government healthcare spending to a performance-based financing approach. Lessons learned from our analysis of the KBK program should provide insights into a broader budgeting scope.

The performance-based capitation or KBK program shows that the primary care providers do respond to the program's incentive, but the response is still far below the set targets. We observe that the reform positively impacted monthly visits and visits related to chronic diseases, whereas the non-specialist referral rate (as measured in our proxy) was not affected. KBK has increased the percentage of enrollees who visit monthly by 0.735 per 100 individuals. However, despite aiming for at least 15 out of every 100 enrollees to have at least one monthly contact, the increase of 0.735 per 100 enrollees in monthly contacts, compared to the baseline of 1.21 per 100 enrollees per month in 2015, still falls significantly short of the target.

According to the Ministry of Health, only 2,962 puskesmas, which is 30% of the total 9,767 puskesmas, can provide healthcare services up to a predefined minimum standard. Given this situation, meeting the specified usage targets might be challenging for these facilities. Therefore, setting lower and more realistic and attainable goals may be more effective, as they are more likely to improve results than setting overly ambitious targets. This thesis advocates the idea that the Indonesian government should initially lower its targets and then progressively increase them periodically. Setting identical targets for all puskesmas may be very discouraging if the goals are unattainable, while well-equipped facilities require less effort to meet KBK targets. Using benchmarks or previous achievements as a basis for setting facility-specific targets could provide greater motivation for improvement.

Enhancing healthcare system resilience for natural disasters

Common responses to natural disasters have predominantly been reactive in the LMICs, including Indonesia. Therefore, enhancing disaster responsiveness requires the policymaker community to increase efforts in implementing proactive preparedness and readiness measures (Ciottone & Salio, 2023). The impacted population's engagement in mitigation efforts tends to be minimal, aligning with the perception that the public's risk assessment for the impact of forest fire is low (Aiyuda, 2016).

Our Chapter 5 findings indicate that a reduction of general hospital treatment for children after the 2015 forest fire raises concerns, particularly in the context of unmet healthcare needs beyond respiratory issues. While investigating potential long-term health consequences was not feasible with our data, there is a possibility that needed care was foregone both during and after the forest fire. An obvious implication for health policy is that increased attention is required to address essential care needs for children, particularly in rural areas, during the post-fire period. Our findings reveal an immediate, yet not statistically significant, increase of 1.42 visits to primary care facilities in forest fire-affected districts. Additionally, we observe a delayed increase of 3.13 visits per 1,000 under-five enrollees in total primary care visits after the forest fire period. This translates to a 17% rise in total primary care visits following a forest fire compared to pre-fire levels.

When examining the health reasons behind outpatient visits, we identify statistically significant effects emerging after the forest fire period, particularly for respiratory diseases (an increase of 2.41 visits per 1,000) and common cold cases (an increase of 2.14 visits per 1,000), resulting in respective increases of 22% and 43%. We observed contrasting outcomes in the utilization of hospitals for under-five individuals, with visit rates decreasing by 3.26 during the forest fires and by 5.15 afterwards. These reductions represent a 10% and 16% decline relative to pre-fire utilization levels in the affected districts. Notably, and perhaps reassuringly, we did not observe any noticeable impact of the forest fire on healthcare utilization among the population over the age of five.

Our regional analysis indicates that the influence of forest fires on primary healthcare is primarily associated with changes in urban areas rather than rural ones, even though most of the fires occur in rural and remote areas (Edwards et al., 2020). For instance, we consistently found positive effects of forest fires on primary care overall usage, as well as respiratory disease and common cold cases in children under five in urban locations. However, when it comes to hospital treatment, we observed negative effects in urban and rural districts, with estimates being less precise for urban areas.

Methodological issues or limitations of the thesis

The studies in this thesis also encountered some methodological and data challenges. First, JKN was introduced simultaneously across the entire population (Cabinet Secretariat of the Republic of Indonesia, 2014), which presents challenges in establishing a control group for assessing its impact on healthcare utilization. In Chapter 2, we employ the share of health insurance ownership as a proxy for the intensity of JKN's implementation. While this approach may not provide the most robust causal inference for JKN, it allows us to examine the association between JKN ownership and healthcare utilization.

Second, we encounter a challenge known as the portability principle in the JKN (Ministry of Health, 2016b) in Chapter 3. This principle permits patients to seek healthcare in hospitals located in different districts, provinces, or islands in case of a medical emergency. This aspect poses a limitation to our Benefit Incidence Analysis (BIA) in terms of regional distributions. It is important to note that the district receiving a JKN payout may not always correspond to the patient's residence, as the patient might seek care in a different district. Unfortunately, we cannot account for cross-district healthcare utilization due to data limitations.

A second data availability constraint is that, ideally, we would have preferred to use puskesmas-level data rather than relying on average district-level statistics in Chapter 4. Unfortunately, puskesmas-level data was not publicly available. Nevertheless, conducting a district-level study in primary care holds its own benefits because KBK implementation began at the district level. District-level policies can significantly influence the impact of KBK, as each district's local government has the authority to allocate the health budget and determine the proportion of capitation in its puskesmas.

Chapter 4 of our study also faced several data constraints. The first limitation arises from the exclusion of healthcare promotion meetings in our estimates. These meetings are part of KBK's contact rate performance metric, but we could not include them due to data constraints. Consequently, our contact rate estimates may significantly underestimate the extent to which some puskesmas achieve their intended contact rates.

When examining the impact of forest fires on healthcare utilisation, one data limitation must be considered in Chapter 5. Firstly, the Aerosol Optical Depth (AOD) data per district serves as a proxy measure for PM2.5 concentrations, which have been used in various other health studies. However, it is important to note that issues such as cloud contamination, differing surface conditions, or retrieval inaccuracies from satellite data may result in inaccuracies or gaps in the AOD values. These factors could potentially introduce a downward bias into our effect estimates.

Recommendations for future research

This dissertation has presented an overview of the JKN program and identified some problems that persist even after the changes it brought. We explored how healthcare benefits are distributed before and after the JKN, how performance-based capitation affects the use of primary healthcare services, and how forest fires affect healthcare use for general health and respiratory use in the impacted districts. Even though we can answer some of the research questions in this dissertation, it also raises recommendations and ideas for future research.

One of the significant developments brought by JKN is that the reform has facilitated the availability of more extensive healthcare utilization data for researchers (Pusat Kebijakan dan Manajemen Kesehatan FKKMK UGM, 2019). With the transition to public ownership of healthcare insurance, there is a growing demand for data transparency and evaluation. Consequently, BPJS Kesehatan's data policies are now more open compared to the previous system by opening a data management platform (BPJS Kesehatan, 2018; Fuad, 2019; Hidayat, 2019). However, even with new data available, it is underutilized, as only a few researchers make use of BPJS Kesehatan data for their analyses.

For the purpose of health economics analysis, the data available from BPJS Kesehatan is limited, particularly regarding socioeconomic information and out-of-pocket payments (OOP). In the UHC roadmap, reducing OOP is one of the main aims of health insurance coverage expansion (WHO, 2010a). As researchers, we have to resort to proxies or higher-level district-level analyses using socioeconomic data from other sources, such as Susenas, but it has some disadvantages (Johar et al., 2019). It would greatly benefit healthcare research in Indonesia if BPJS Kesehatan could provide comprehensive data on socioeconomic conditions alongside health indicators.

While conducting the research in this thesis, several aspects that could be valuable for future investigations to consider have come to light. First, our study primarily focuses on healthcare utilization volumes as recorded by BPJS Kesehatan. It would be advantageous if BPJS Kesehatan could also provide data on healthcare quality. We have tried to do so by acquiring customer satisfaction and patient waiting time from surveys such as Health Facility Research (*Risfaskes*) and Healthcare Worker Research (*Risnakes*) data from the Ministry of Health (BKPK Kementerian Kesehatan, 2021). However, due to different sampling frames, we did not successfully construct a panel data set. Ideally, JKN is not solely about access to healthcare; it also encompasses providing high-quality healthcare services (TNP2K, 2015). Therefore, having data on healthcare quality would be beneficial for a more comprehensive assessment.

The insights gained from Chapter 5 open further investigation at the intersection of healthcare data and natural hazards in Indonesia. Given the country's vulnerability to frequent natural disasters, such as earthquakes, volcanic eruptions, floods, and forest fires, there is a compelling need to understand the implications of these events to protect people's well-being (Global Facility for Disaster Reduction and Recovery (GFDRR), 2022). Indonesia has made commendable efforts to document and manage these natural disasters through agencies, such as the National Disaster Management Agency (BNPB) (National Disaster Management Agency (BNPB), 2023) and the Ministry of Forestry and Environment (Ministry of Environment and Forestry, 2023). These organizations collect comprehensive data on the impact of disasters, encompassing affected regions, population demographics, and environmental conditions. However, this effort is fragmented and requires synchronization for more valuable data.

By combining healthcare data from BPJS Kesehatan with this wealth of natural hazard data, researchers and policymakers could gain valuable insights into several critical areas. For instance, they could explore the effectiveness of healthcare responses during and after disasters, identify vulnerable populations, assess healthcare infrastructure readiness, and develop strategies to enhance healthcare preparedness in disaster-prone regions. Overall, the convergence of healthcare and natural hazard data presents an opportunity to understand better the complex dynamics of disaster management and healthcare resilience in Indonesia, ultimately contributing to more effective disaster response and improved healthcare outcomes for the population.

SUMMARY

Several challenges persist in the ongoing efforts to enhance health coverage in Indonesia. First, the unanswered questions revolve around how the consolidation of existing health insurance schemes and the introduction of self-enrolled schemes will effectively increase healthcare utilization, especially for the “missing middle” problem with the uncovered non-poor informal sector. Second, how socioeconomic and geographic disparities further impede equal access and healthcare benefits, with higher-quality clinics and hospitals predominantly concentrated in urban areas, particularly within Java and Bali. Moreover, the concentration of health specialists in these regions exacerbates the issue. Third, as JKN concentrates on enlarging its membership base, the lack of quality in healthcare persists. BPJS Kesehatan has tried to address this concern by implementing performance-based capitation, and an evaluation of its effectiveness in JKN is a vital aspect we aim to explore. Fourth, Indonesia's vulnerability to natural disasters necessitates a resilient health system, prompting an assessment of forest fire impact and its effects on the most affected populations during such events. The new data from BPJS Kesehatan has enabled us to do this assessment. This thesis delves into addressing these research questions.

First, we commence with a brief introduction section to outline the objectives and context of the thesis in Chapter 1. Then, in Chapter 2, we provide an overview of the healthcare reform and the persisting problems. The second objective of Chapter 2 is to investigate the relationship between the growing coverage share and healthcare utilization at the district level. Following the JKN implementation, our findings indicate an increased positive correlation between expanding healthcare insurance coverage and utilization, particularly in hospital care.

Self-enrolled health insurance (SEHI) schemes exhibit the strongest association with hospital care utilization. In contrast, health insurance for the poor (HIFP) reveals a growing positive association with public hospital and hospital inpatient service utilization. The mandatory health insurance (MHI) scheme steadily advances coverage and healthcare use. Despite the option for JKN-covered individuals to access private facilities, non-significant results for private care use in HIFP and MHI schemes suggest infrequent visits to private facilities. On the contrary, self-enrolled usage for private outpatient and inpatient services was rising. Concerns arise about adverse selection, particularly with the growing use of self-enrolled schemes, posing a potential threat to JKN's financial sustainability.

In Chapter 3, our goal is to assess how healthcare funding is distributed in the JKN era, considering its benefit incidence across socioeconomic statuses and regional unit cost variations. We aim to determine whether funding benefits favour urban and wealthier households, evaluate if national unit costs underestimate regional disparities in healthcare funding, and examine if the JKN provider payment system worsens regional inequalities in treatment intensity and value.

Our results reveal that wealthier groups enjoy a more significant benefit incidence from healthcare expenditure, accompanied by considerable variation in hospital unit costs across Indonesian regions. The use of national average unit transfers in standard benefit incidence analysis underestimates inequality due to regional healthcare supply and treatment value disparities. The JKN provider payment system appears to favor wealthier regions with advanced healthcare services, leading to greater healthcare benefit incidence for urban residents, such as those in Java and Bali, compared to rural areas and other islands.

In Chapter 4, we assess one of the first initiatives to integrate capitation-based payments with performance-based financing—the *Kapitasi Berbasis Kinerja* (KBK) scheme for community health centers (puskesmas), implemented in provincial capitals from August 2015 to May 2016. The primary objective was to incentivize the shift from secondary to primary care utilization. We examine the impact on three incentivized outcomes: the proportion of insured individuals visiting puskesmas, the proportion of chronically ill patients with puskesmas visits, and the hospital referral rate for insured individuals with non-specialistic conditions.

Our findings in Chapter 4 indicate that KBK payments increased the monthly number of visits to puskesmas but fell short of reaching the program's "sufficient" threshold for most puskesmas. For visits by chronically ill patients, there was a slight increase, but still below the program's "sufficient" threshold. No statistically significant effect was observed on referral rates to hospitals for conditions not requiring specialist care. While positive effects were identified for two out of three outcomes, all estimated effect sizes remained considerably below the program targets. Overall, our findings suggest that the KBK performance-based capitation reform has not been highly successful in promoting greater primary care utilization as a substitute for secondary care.

In Chapter 5, we explore the impact of the 2015 forest fires in Indonesia on healthcare utilization among the affected population. Our analysis focuses on the immediate health effects, estimating visit rates to primary care and hospitals, considering three specific smoke-related conditions (respiratory disease, acute respiratory tract infection (ARTI), and common cold).

We find limited effects observed for members over the age of five years old, while positive impacts are noted for young children seeking care for respiratory issues in urban primary healthcare facilities. Conversely, hospital care visits experience a negative impact in rural areas overall. We posit that these patterns arise from the constrained care accessibility during forest fires, particularly in rural settings. The primary implication for health policy underscores the necessity for heightened attention in the post-fire period, specifically to ensure the timely provision of essential healthcare for children, especially in rural areas.

In the final discussion section, we consolidate policy recommendations derived from the main findings across various studies in the thesis. We outline methodological challenges encountered and propose new ideas for future research stemming from the insights gained while writing this thesis.

SAMENVATTING

Er blijven uitdagingen te bestaan om de dekking voor de zorgkosten in Indonesië te verbeteren. Ten eerste draaien de onbeantwoorde vragen of de consolidatie van de bestaande ziektekostenverzekeringen en de introductie van zelf ingeschreven regelingen de effectiviteit van de gezondheidszorg beter worden, vooral voor de modaal inkomsten. Ten tweede, door de sociaaleconomische en geografische verschillen de gezondheidszorgvoordelen verder belemmeren, waarbij klinieken en ziekenhuizen van hogere kwaliteit voornamelijk geconcentreerd zijn in stedelijke gebieden, vooral op Java en Bali. Bovendien de concentratie van gezondheidsspecialisten in deze regio's verergeren het probleem. Ten derde blijft er het gebrek aan kwaliteit in de gezondheidszorg te bestaan doordat het JKN legt meer de focus op het vergroten van haar ledenbestaan. BPJS Kesehatan heeft geprobeerd dit probleem aan te pakken door op de prestaties gebaseerde capitatie te implementeren en de effectiviteit daarvan te evalueren voor JKN is een essentieel aspect voor nader onderzoek. Ten vierde Indonesië is door kwetsbaarheid voor de natuurrampen een veerkrachtig gezondheidszorgsysteem nodig, wat aanleiding geeft tot een beoordeling van de gevolgen van bosbranden en de gevolgen daarvan voor de meest getroffen bevolkingsgroepen tijdens dergelijke gebeurtenissen. De nieuwe gegevens van BPJS Kesehatan hebben ons in staat gesteld deze beoordeling uit te voeren. Dit proefschrift gaat dieper in op het beantwoorden van deze onderzoeksvragen.

Eerst beginnen we met een kort introductiegedeelte om de doelstellingen en context van het proefschrift in hoofdstuk 1 te schetsen. Vervolgens geven we in hoofdstuk 2 een overzicht van de hervorming van de gezondheidszorg en de aanhoudende problemen. De tweede doelstelling van Hoofdstuk 2 is het onderzoeken van de relatie tussen het groeiende dekkingsaandeel en het zorggebruik op districtsniveau. Na de implementatie van de JKN duiden onze bevindingen op een toegenomen positieve correlatie tussen de uitbreiding van de dekking van de zorgverzekering en het gebruik ervan, vooral in de ziekenhuiszorg.

Zelf ingeschreven ziektekostenverzekeringen (SEHI) vertonen de sterkste associatie met het gebruik van ziekenhuiszorg. De ziektekostenverzekering voor de armen (HIFP) laat daarentegen een groeiend positief verband zien met het gebruik van openbare ziekenhuizen en ziekenhuisopnames. De verplichte ziektekostenverzekering (MHI) verbetert de dekking en gebruik van gezondheidszorg geleidelijk. Ondanks de mogelijkheid voor door onder JKN-gedekte particulieren om toegang te krijgen tot privévoorzieningen, duiden niet-significante resultaten voor het gebruik van particuliere zorg in HIFP- en MHI-programma's op onregelmatige bezoeken aan particuliere voorzieningen. Integendeel, het zelf ingeschreven gebruik voor particuliere ambulante en intramurale diensten nam toe. Er ontstaan zorgen over averechtse selectie, vooral door het toenemende gebruik van zelf ingeschreven regelingen, die een potentiële bedreiging vormt voor de financiële duurzaamheid van JKN.

In Hoofdstuk 3 is ons doel om te beoordelen hoe de financiering van de gezondheidszorg in het JKN-periode is verdeeld, waarbij rekening wordt gehouden met zijn incidentiele voordelen op de sociaaleconomische statussen en de regionale variaties in de kosten per eenheid. Ons doel is vast te stellen of de financieringsvoordelen gunstig zijn voor stedelijke en rijkere huishouders, te evalueren of de nationale kosten per eenheid de regionale verschillen in de financiering van de gezondheidszorg onderdrukken, en te onderzoeken of het betalingssysteem van de JKN-aanbieder de regionale ongelijkheid in behandelingsintensiteit en -waarde erger maakt.

Uit onze resultaten is gebleken dat rijkere groepen een groter voordeel hebben uit de gezondheidszorguitgaven, gepaard gaande met aanzienlijke verschillen in de kosten van ziekenhuiseenheden in de Indonesische regio's. Het gebruik van nationale gemiddelde eenheidsoverdrachten in de standaardanalyse van uitkeringsincidentie onderdrukt de ongelijkheid als gevolg van regionale verschillen in het gezondheidszorgaanbod en de behandelingswaarde. Het betalingssysteem van de JKN-aanbieder lijkt de voorkeur te geven aan rijkere regio's met geavanceerde gezondheidszorgdiensten, wat leidt tot een grotere kans op gezondheidszorguitkeringen voor stadsbewoners, zoals die op Java en Bali, vergeleken met plattelandsgebieden en andere eilanden.

In hoofdstuk 4 beoordelen we een van de eerste initiatieven om kapitaal gebaseerde betalingen te integreren met prestatie gebaseerde financiering: het Kapitasi Berbasis Kinerja (KBK)-programma voor gemeenschapsgezondheidscentra (puskesmas), geïmplementeerd in provinciehoofdsteden van augustus 2015 tot mei 2016. Het primaire doel was om de verschuiving van het gebruik van secundaire naar eerstelijnszorg te stimuleren. We onderzoeken de impact op drie voordelige uitkomsten: het percentage van de verzekerden dat puskesmas bezoekt, het percentage van de patiënten met chronisch zieke dat puskesmas bezoekt, en het percentage verwijzingen naar ziekenhuizen voor verzekerden met niet-specialistische aandoeningen.

Onze bevindingen in Hoofdstuk 4 geven aan dat KBK-betalingen bijdragen aan de toename van het maandelijkse aantal bezoeken aan puskesmas maar niet voldoende om het programma te bereiken voor de meeste puskesmas. Voor bezoeken van chronisch zieke patiënten was er een lichte stijging, maar nog steeds onder de drempel van "voldoende" in het programma. Er is geen significant effect waargenomen op het aantal verwijzingen naar ziekenhuizen voor aandoeningen waarvoor geen specialistische zorg nodig was. Hoewel voor twee van de drie uitkomsten positieve effecten werden vastgesteld, bleven alle geschatte effectgroottes aanzienlijk onder de programmadoelstellingen. Over het geheel genomen suggereren onze bevindingen dat de prestatie gebaseerde capitatie-hervorming van de KBK niet erg succesvol is geweest in het bevorderen van een groter gebruik van de eerstelijnszorg als vervanging voor de tweedelijnszorg.

In hoofdstuk 5 onderzoeken we de impact van de bosbranden van 2015 in Indonesië op het gebruik van gezondheidszorg onder de getroffen bevolking. Onze analyse richt zich op de onmiddellijke gevolgen voor de gezondheid waarbij het aantal bezoeken aan de eerstelijnszorg en ziekenhuizen worden ingeschat rekening houden met drie specifieke rook gerelateerde aandoeningen (luchtwegaandoeningen, acute luchtweginfectie (ARTI) en verkoudheid). Er zijn beperkte effecten waargenomen voor leden ouder dan vijf jaar, terwijl positieve effecten worden opgemerkt voor jonge kinderen die zorg zoeken voor ademhalingsproblemen in stedelijke basisgezondheidszorginstellingen. Omgekeerd ervaren ziekenhuisbezoeken een negatieve impact op het platteland in het algemeen. Wij stellen dat deze patronen voortkomen uit de beperkte toegankelijkheid van zorg tijdens bosbranden, vooral op het platteland. De belangrijkste implicatie voor het gezondheidsbeleid benadrukt de noodzaak van meer aandacht in de periode na de brand, met name om de tijdige verstrekking van essentiële gezondheidszorg voor kinderen te garanderen, vooral in plattelandsgebieden.

In het laatste discussiegedeelte consolideren we beleidsaanbevelingen die zijn afgeleid van de belangrijkste bevindingen uit verschillende onderzoeken in het proefschrift. We schetsen de methodologische uitdagingen die we tegenkomen en stellen nieuwe ideeën voor toekomstig onderzoek voor die voortkomen uit de inzichten die zijn verkregen tijdens het schrijven van dit proefschrift.

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APPENDIX

A. Appendix – The Indonesian National Health Insurance (Jaminan Kesehatan Nasional) coverage and healthcare Utilization

Table A1. Law and Regulation on JKN and BPJS Kesehatan

Republic of Indonesia Constitution Pasal 28 Ayat (1), (2), and (3) Pasal 34 Ayat (1), (2), and (3)	
Law No 40 Year 2004 on SJSN **Law** No 24 Year 2011 on BPJS	
Government Regulation No 101/2012; No 86/2013	**Government Regulation** No 82/2013; No 85/2013; No 87/2013; No 88/2013
Presidential Regulation No 12/2013; No 107/2013; No 111/2013; No 23/2014	**Presidential Regulation** No 108/2013; No 110/2013
MoH Regulation No 71/2013; No 19/2014; No 27/2014; No 28/2014; No 59/2019	**MoH Regulation** No 2015/2013; No 206/2013; No 211/2013
BPJS Kesehatan Regulation No 1/2014; No 2/2014	
JKN Regulation	**BPJS Kesehatan Regulation**

Table A2. Progress of health insurance coverage; 2005 - 2018

Scheme	2005	2008	2012	2014	2015	2016	2017	2018
Askes	14.612.789	13.619.991	17.274.520					
Asabri	NA	2.000.000	2.200.000					
Jamsostek	4.515.254	5.393.151	5.600.000					
Jamkesmas	66.233.471	76.400.000	76.400.000					
Jamkesda	NA	10.800.000	31.866.390					
Askes Komersial			2.856.539					
BPJS Kesehatan, PBI								
APBN				86.400.000	86.434.803	90.801.515	91.151.594	92.244.075
APBD				3.850.012	10.619.221	12.934.289	15.804.931	27.394.906
BPJS Kesehatan, Non PBI								
Pekerja Penerima Upah (PPU) - [1]b				13.340.743	14.769.695	15.525.866	16.065.015	17.145.806
Pekerja Penerima Upah (PPU) - [2]c				8.187.216	19.547.610	23.071.743	24.981.345	31.436.014
Pekerja Bukan Penerima Upah (PBPU)				856.464	12.891.474	15.993.399	19.569.848	29.946.318
Non Worker				4.919.100	4.909.362	4.999.168	5.063.886	5.117.777
Total Coverage	85.361.514	108.213.142	136.197.449	117.553.535	149.172.165	163.325.980	172.636.619	203.284.896
Indonesian Population	213.375.000	228.500.000	245.400.000	252.200.000	255.500.000	258.700.000	261.900.000	271.100.000
Health Insurance Coverage (%)	40,0	47,4	55,5	46,6	58,4	63,1	65,9	75,0

Source: Modified from Fuady (2019). Note: NA: Not Available; [b] PPU for govt officials, military and police; [c] PPU for SOE and Private company staffs.
Health insurance coverage for 2005, 2008, and 2012 derived from Indonesian Health Profile (MoH). JKN coverage derived from BPJS Kesehatan (28/02/14; 24/07/2015; 11/03/2016; 13/01/2017; dan 8/10/2018). Population data cited from BPS.

Table A3. Number of Facilities BPJS Kesehatan 2014 -2018

Health Facility	2014	2015	2016	2017	2018
Primary Care					
Puskesmas	9,419	9,805	9,813	9,842	9,903
General Practitioner	3,687	4,143	4,485	4,883	5,151
Klinik Pratama/Primary Clinic	2,682	3,889	4,829	5,834	6,356
Dentist	945	1,011	1,164	1,188	1,214
RS Kelas D Pratama	NA	8	13	16	24
Hospital Care					
Hospital	1,613	1,751	1,807	2,000	2,207
Klinik Utama	68	96	116	197	236
Apotek/Pharmacy	NA	NA	1,966	2,300	1,550
Optik/Optician	NA	NA	939	1,000	1,093

[a] Source: Modified from Fuady (2019). NA: Not Available. Puskesmas: Primary Health Center; RS Kelas D Pratama: Hospital but only offer primary care. Klinik Utama: Klinik with specialist practices

B. Appendix - Does geographic spending variation exacerbate healthcare benefit inequality? A benefit incidence analysis for Indonesia

Appendix Tables

Table B1. Summary statistics of linked data between JKN hospital claim/capitation fund and SUSENAS (2015-2017)

Name of Variable	# observations	Mean	SD	Min	Max
Individual Level Data (SUSENAS)					
Average Per Capita Expenditure per month (USD) in SUSENAS	3,164,933	70.887	68.646	6.34	4,946.15
HH member using outpatient service in the last month (Yes=1; No=0)	3,164,933	0.149	0.356	0	1
Outpatient service in hospital in the last month (Yes=1; No=0)	3,164,933	0.020	0.139	0	1
Outpatient service in primary care in the last month (Yes=1; No=0)	3,164,933	0.128	0.334	0	1
HH member using inpatient service in the last year (Yes=1; No=0)	3,164,933	0.028	0.165	0	1
Number of inpatient days	3,164,933	0.169	1.654	0	364
Inpatient care in hospital in the last year (Yes=1; No=0)	3,164,933	0.030	0.170	0	1
inpatient care in primary care in the last year (Yes=1; No=0)	3,164,933	0.008	0.089	0	1
Living in urban are (Yes=1; No=0)	3,164,933	0.445	0.497	0	1
Municipality=1; District=0	3,160,271	0.208	0.406	0	1
Java-Bali=1; Non Java-Bali=0	3,164,933	0.336	0.472	0	1
District Level Data (BPJS-Kesehatan)					
Unit Cost for Hospital Inpatient visit per District (BPJS-Kesehatan data) (USD)	1,402	234.32	68.75	82.39	764.41
Unit cost for Hospital Outpatient visit per District (BPJS-Kesehatan data) (USD)	1,400	14.91	4.04	0.02	37.46
Unit cost for Primary Care Outpatient visit per District (BPJS-Kesehatan data + Susenas) (USD)	1,405	4.61	4.69	0.66	129.50

Table B2. Concentration index comparison using national unit cost vs. district-specific unit cost (2017)

Variable	DUC			NUC			DUC-NUC	
	CI	SE	p-value	CI	SE	p-value	CI	p-value
	1	2	3	4	5	6	7	8
Hospital Outpatient (HO) Benefit	0.335	0.007	0.000	0.307	0.007	0.000	0.028	0.000
Hospital Inpatient (HI) Benefit	0.269	0.005	0.000	0.229	0.005	0.000	0.040	0.000
Primary Care Outpatient (PO) Benefit	0.039	0.002	0.000	0.001	0.002	0.526	0.038	0.000
Total Healthcare Financing Benefit	0.211	0.003	0.000	0.178	0.003	0.000	0.033	0.000

Source: Authors' analysis based on SUSENAS 2017 and BPJS-*Kesehatan* administrative data.

Table B3. Concentration Index of healthcare financing benefit distribution (2015-2017)

Variable	2015 (SE) [p-value]	2016 (SE) [p-value]	2017 (SE) [p-value]	Diff:2016-2015 (SE) [p-value]	Diff:2017-2016 (SE) [p-value]	Diff:2017-2015 (SE) [p-value]
Using National Unit Cost (NUC)						
Hospital Outpatient Benefit	0.305	0.294	0.307	-0.012	0.014	0.002
	0.006	0.006	0.007	0.008	0.009	0.009
	0.000	0.000	0.000	0.166	0.125	0.824
Hospital Inpatient Benefit	0.243	0.243	0.229	0.000	-0.014	-0.014
	0.005	0.005	0.005	0.007	0.007	0.007
	0.000	0.000	0.000	0.932	0.028	0.038
Primary Care Outpatient Benefit	-0.004	-0.003	0.001	0.001	0.005	0.006
	0.002	0.002	0.002	0.003	0.003	0.003
	0.019	0.074	0.526	0.765	0.097	0.045
Total Healthcare Financing Benefit	0.209	0.210	0.213	0.001	0.003	0.004
	0.004	0.003	0.004	0.005	0.005	0.005
	0.000	0.000	0.000	0.889	0.523	0.438
Using District Unit Cost (DUC)						
Hospital Outpatient Benefit	0.343	0.328	0.335	-0.015	0.007	-0.008
	0.007	0.007	0.007	0.009	0.010	0.010
	0.000	0.000	0.000	0.119	0.480	0.426
Hospital Inpatient Benefit	0.288	0.281	0.269	-0.007	-0.012	-0.019
	0.005	0.005	0.005	0.008	0.008	0.008
	0.000	0.000	0.000	0.403	0.115	0.017
Primary Care Outpatient Benefit	0.025	0.027	0.039	0.001	0.013	0.014
	0.002	0.002	0.002	0.003	0.003	0.003
	0.000	0.000	0.000	0.650	0.000	0.000
Total Healthcare Financing Benefit	0.210	0.206	0.211	-0.005	0.005	0.001
	0.003	0.003	0.003	0.005	0.005	0.005
	0.000	0.000	0.000	0.317	0.261	0.908

Source: Authors' analysis based on SUSENAS 2015-2017 and BPJS-*Kesehatan* administrative data..

Table B4. Healthcare financing benefit share based on geographic location (2015-2017)

Geographic Location		H0			HI			PO			Total		
		2015	2016	2017	2015	2016	2017	2015	2016	2017	2015	2016	2017
Rural vs Urban													
Share Benefit (%)	Rural	26.3	28.6	26.3	32.8	32.6	30.9	47.1	45.2	44.4	36.1	35.9	34.2
	Urban	73.7	71.4	73.7	67.2	67.4	69.1	52.9	54.8	55.6	63.9	64.1	65.8
Average odds	Rural	0.54	0.60	0.57	0.67	0.68	0.67	0.97	0.95	0.96	0.74	0.75	0.74
	Urban	1.44	1.37	1.37	1.31	1.29	1.29	1.03	1.05	1.03	1.25	1.23	1.22
Non Java-Bali Vs Java-Bali													
Share Benefit (%)	Non Java-Bali	31.0	31.9	30.6	32.3	32.8	32.2	35.7	36.4	37.5	33.1	33.8	33.5
	Java-Bali	69.0	68.1	69.4	67.7	67.2	67.8	64.3	63.6	62.5	66.9	66.2	66.5
Average odds	Non Java-Bali	0.76	0.79	0.75	0.80	0.81	0.79	0.88	0.90	0.92	0.82	0.83	0.82
	Java-Bali	1.16	1.15	1.17	1.14	1.13	1.15	1.08	1.07	1.06	1.13	1.11	1.12
Other Islands													
Share Benefit (%)	Sumatera	17.7	18.5	17.3	16.9	16.7	16.8	19.9	19.8	19.7	18.09	18.20	17.84
	NTB and NTT	2.4	2.0	2.3	2.5	2.3	2.3	3.4	3.0	3.5	2.72	2.46	2.67
	Kalimantan	4.4	4.6	4.3	5.0	5.5	5.0	5.0	5.1	5.7	4.87	5.15	5.06
	Sulawesi	5.0	5.2	5.1	6.5	6.9	6.8	5.0	6.4	6.3	5.65	6.33	6.31
	Maluku and Papua	1.5	1.6	1.6	1.3	1.4	1.3	2.4	2.1	2.3	1.76	1.68	1.64
Average odds	Sumatera	0.82	0.85	0.78	0.79	0.77	0.76	0.92	0.91	0.89	0.84	0.83	0.81
	NTB and NTT	0.64	0.52	0.60	0.66	0.61	0.60	0.89	0.79	0.91	0.73	0.65	0.69
	Kalimantan	0.75	0.77	0.68	0.86	0.93	0.79	0.85	0.86	0.91	0.83	0.87	0.81
	Sulawesi	17.7	18.5	17.3	16.9	16.7	16.8	19.9	19.8	19.7	18.09	18.20	17.84
	Maluku and Papua	2.4	2.0	2.3	2.5	2.3	2.3	3.4	3.0	3.5	2.72	2.46	2.67

Note: We use district unit costs to produce healthcare benefit shares. The average odds are a result of dividing shares of healthcare financing benefit received in a group by the share of its population to total population. We use population estimates from SUSENAS.

Table B5. Total healthcare financing benefit concentration index disparities based on geographical location (2015-2017)

Variable	2015 (SE) [p-value]	2017 (SE) [p-value]	Diff:2017-2015 (SE) [p-value]
Using District Unit Cost (DUC)			
Urban	0.251	0.254	0.003
	0.006	0.006	0.009
	0.000	0.000	0.753
Rural	0.190	0.200	0.009
	0.005	0.005	0.007
	0.000	0.000	0.176
Kota (Municipalities)	0.152	0.145	-0.007
	0.008	0.007	0.011
	0.000	0.000	0.513
Kabupaten (District)	0.206	0.225	0.018
	0.004	0.005	0.006
	0.000	0.000	0.004
Java-Bali	0.320	0.312	-0.008
	0.007	0.007	0.010
	0.000	0.000	0.350
Outside Java-Bali	0.275	0.297	0.022
	0.007	0.007	0.010
	0.000	0.000	0.024
Sumatera	0.282	0.291	0.009
	0.007	0.010	0.014
	0.000	0.000	0.509
NTB and NTT	0.248	0.329	0.081
	0.017	0.022	0.028
	0.000	0.000	0.003
Kalimantan	0.284	0.311	0.027
	0.016	0.015	0.022
	0.000	0.000	0.213
Sulawesi	0.288	0.300	0.013
	0.018	0.016	0.024
	0.000	0.000	0.596
Maluku and Papua	0.236	0.283	0.046
	0.016	0.016	0.023
	0.000	0.000	0.042

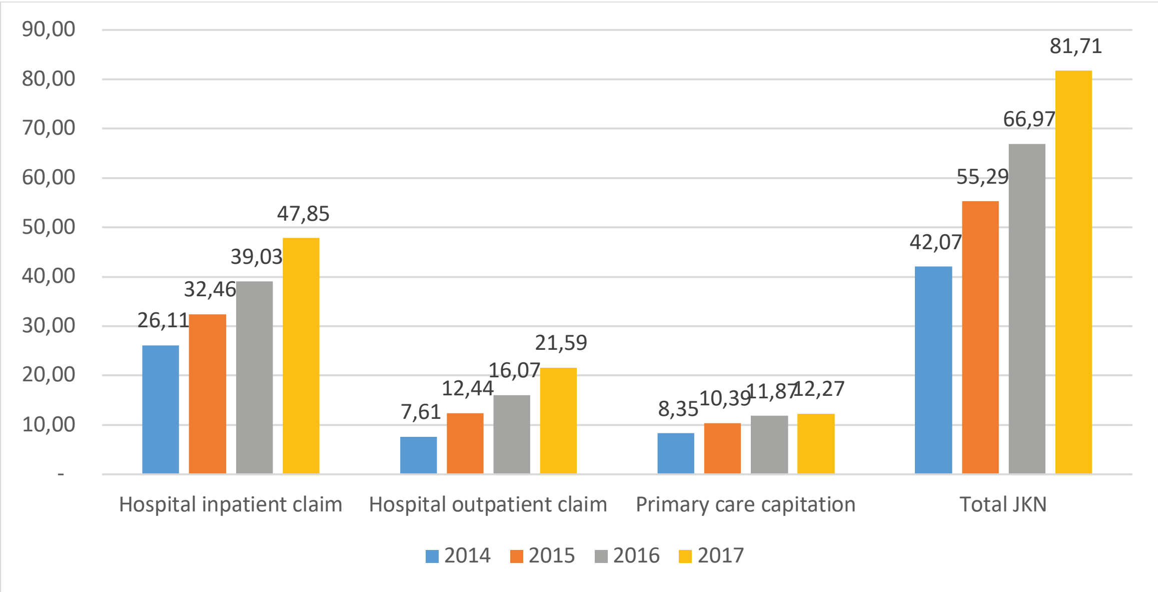
Source: Authors' analysis based on SUSENAS 2015-2017 and BPJS-*Kesehatan* administrative data.

Table B6. Distribution of healthcare utilization share across socioeconomic quintiles (2015-2017) (Based on Utilization Rate)

	Hospital Inpatient				Hospital Outpatient				Primary Care Outpatient			
	Inpatient days per 100 individuals in one year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)	Outpatient visit per 100 individuals in a year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)	Outpatient visit per 100 individuals in a year	Share (%)	Unit Cost (USD)	Benefit Share % (district unit costs)
	1	2	3	4	5	6	7	8	9	10	11	12
2015												
Poorest	6.61	11.37	55.29	10.22	NA				NA			
2nd quintile	7.54	12.53	60.85	11.39	NA				NA			
3rd quintile	10.12	17.26	59.36	16.14	NA				NA			
4th quintile	14.03	22.21	63.89	22.11	NA				NA			
Richest	21.95	36.63	63.25	40.14	NA				NA			
Mean	11.50	100.00	60.54	100.00	NA				NA			
2016												
Poorest	5.61	9.54	59.44	8.53	NA				NA			
2nd quintile	7.92	13.63	58.35	12.71	NA				NA			
3rd quintile	9.69	16.46	57.07	15.36	NA				NA			
4th quintile	14.06	23.93	61.14	23.79	NA				NA			
Richest	21.33	36.44	62.42	39.61	NA				NA			
Mean	11.74	100.00	59.91	100.00	NA				NA			
2017												
Poorest	9.72	9.83	38.15	8.82	17.90	8.72	7.98	8.13	194.42	18.95	2.62	17.45
2nd quintile	13.44	13.61	39.65	12.84	28.43	13.27	7.40	12.68	208.03	20.17	2.65	19.20
3rd quintile	16.21	16.78	40.07	15.99	32.23	15.65	7.57	15.01	216.70	21.19	2.69	21.19
4th quintile	21.89	22.92	38.66	22.45	44.38	22.17	7.76	21.85	221.77	21.53	2.77	21.96
Richest	36.01	36.86	38.82	39.90	83.67	40.20	8.12	42.33	193.40	18.16	2.93	20.20
Mean	20.31	100.00	38.91	100.00	43.43	100.01	8.04	100.00	206.94	100.00	2.78	100.00

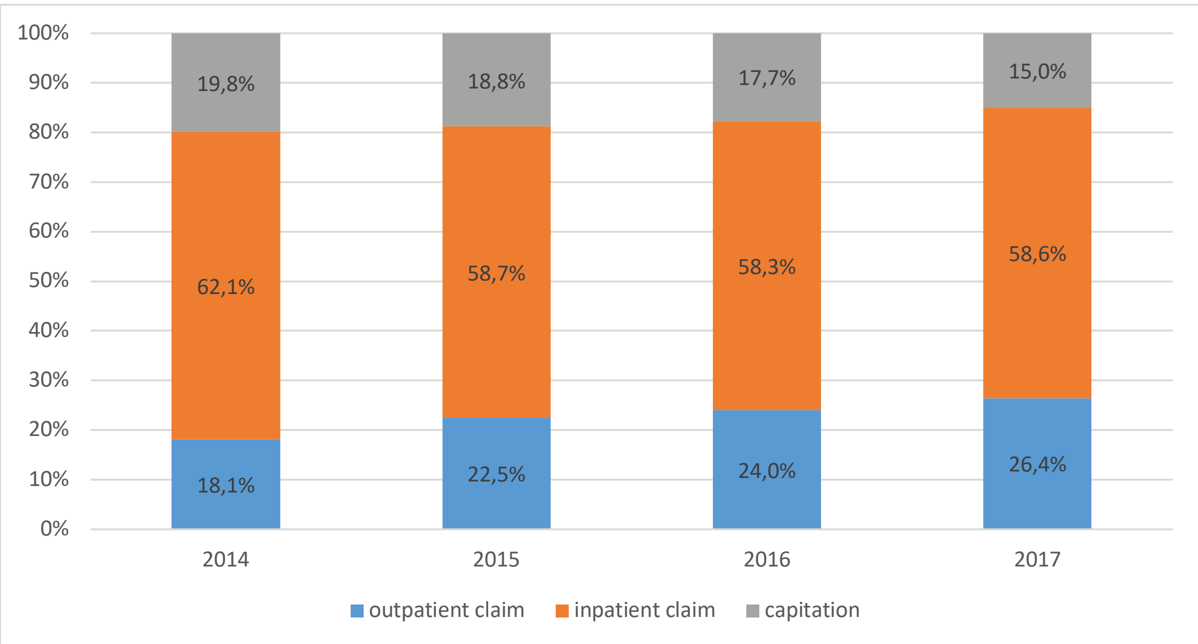
Note: Outpatient visit (hospital and primary care) annualized by multiply them by twelve

Figure B1. Total amount of JKN fund disbursed 2014-2017 (trillion IDR)



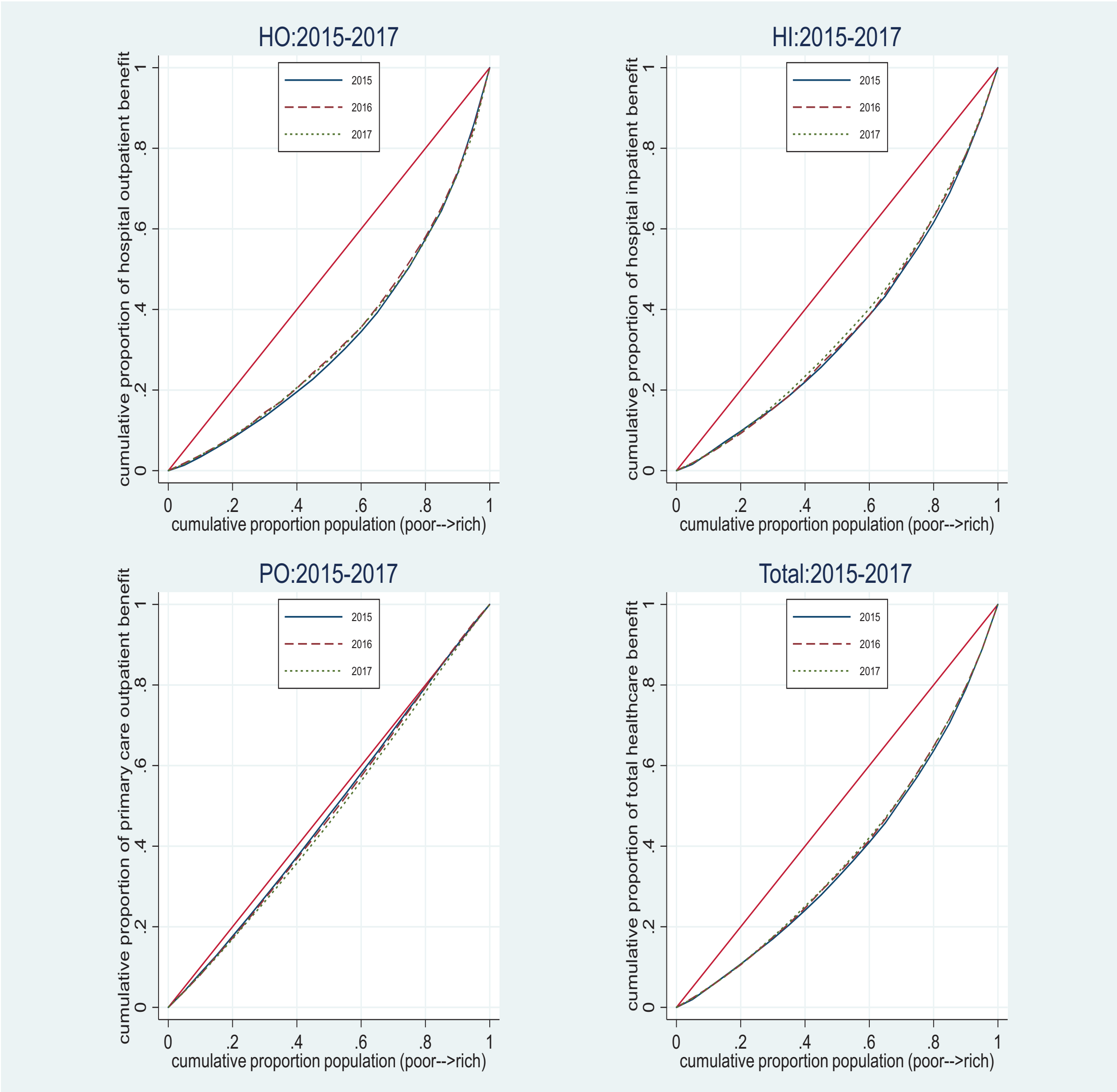
Source: Authors' analysis based on BPJS-*Kesehatan* fund distribution by districts.

Figure B2. Distribution of JKN fund disbursed by type of service 2014-2017



Source: Authors' analysis based on BPJS-*Kesehatan* fund distribution by districts.

Figure B3. Concentration curves for cumulative share of hospital (outpatient and inpatient) and primary care (outpatient) benefit weighted by district unit costs (2015-2017)



Note: The y-axis plots the cumulative density of healthcare benefits by individuals ranked from the least to highest per capita expenditure per year.

Figure B4. Concentration Curve Comparison of Benefit using National Unit Cost vs District Unit Cost (based on utilization rate)

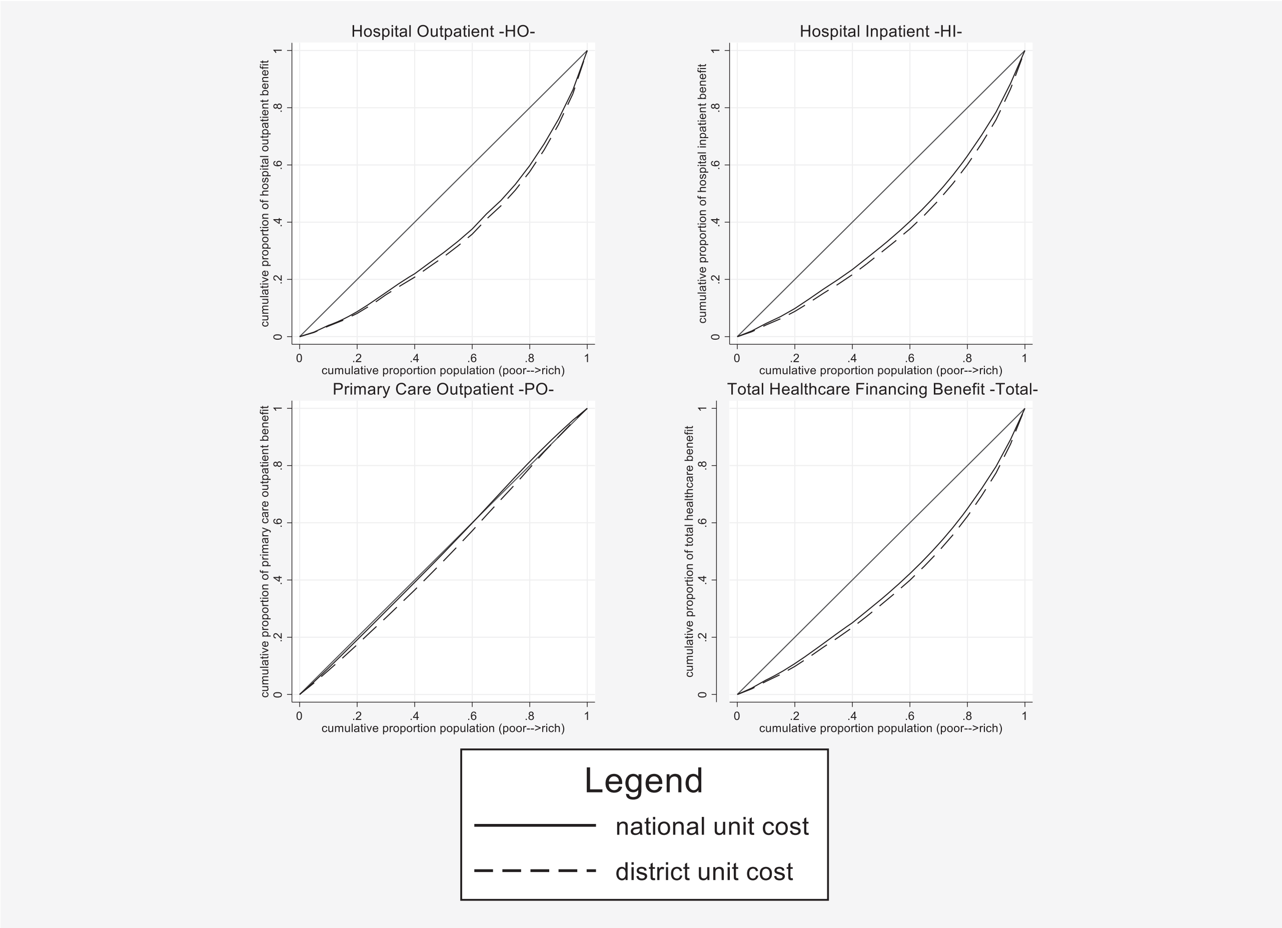


Figure B5. Concentration Curve of hospital inpatient benefit comparison over three years (2015-2017) (based on utilization rate)

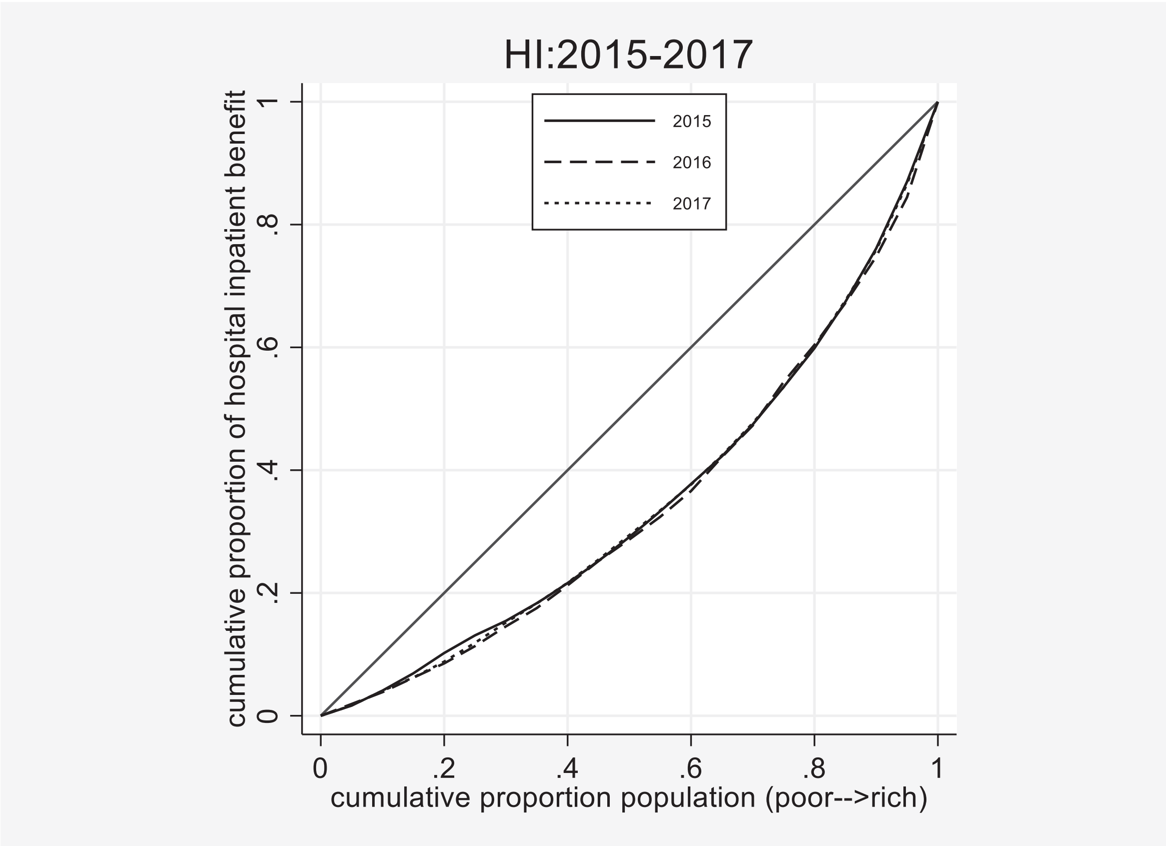
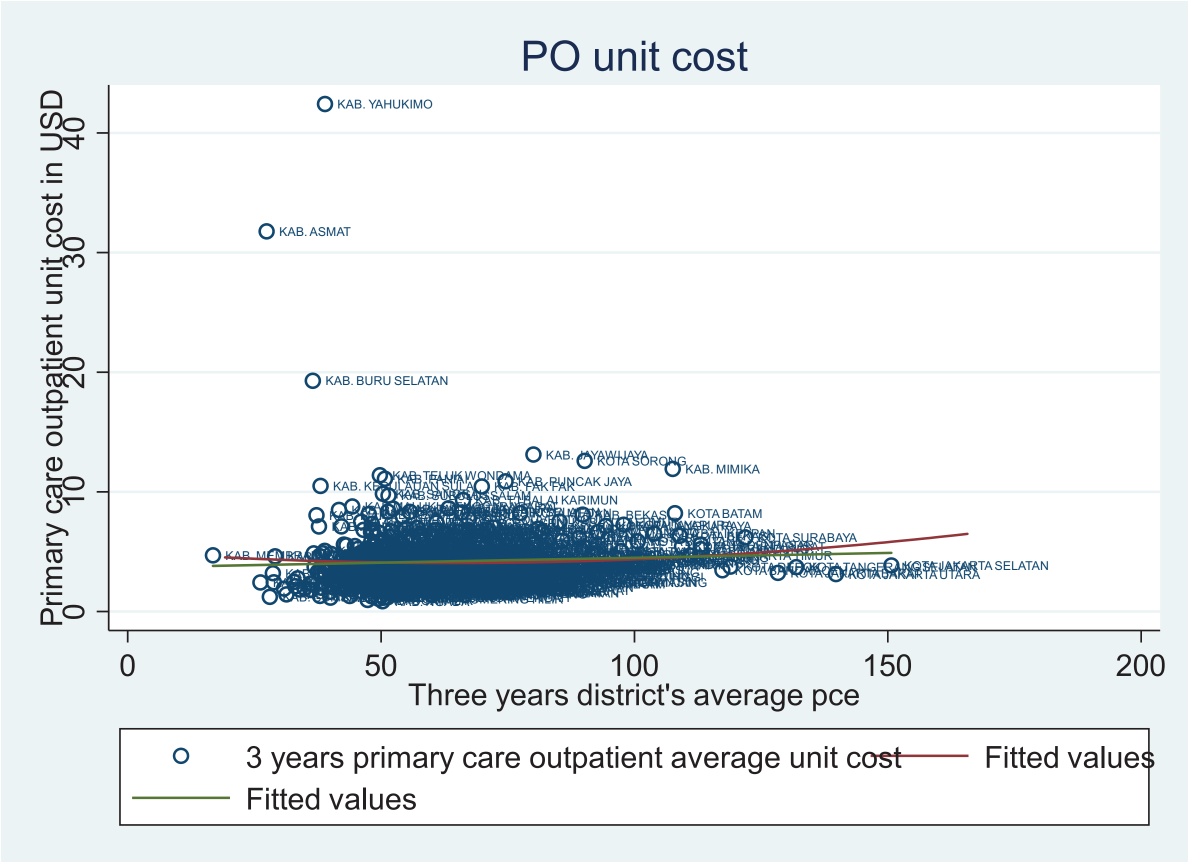


Figure B6. Primary care outpatient (PO) unit cost in district level (2015-2017)



Note: PO refers to primary care outpatient. The Y-axis shows three years averages of district specific unit costs derived from the BPJS-Kesehatan records on capitation fund and primary care outpatient cases per district. The X-axis shows three years district averages of per capita expenditure derived from SUSENAS 2015-2017.

C. Appendix - Effects of performance-based capitation on the use of primary health care services in Indonesia

Appendix Tables

Table C1. Sources of revenue for Puskesmas

Year	2013	2014	2015
Annual average revenue (USD)	22,538	50,692	81,230
Local Government Insurance (Jamkesda)	6%	5%	2%
Maternity Care Insurance (Jampersal)	20%	0%	0%
Social Health Insurance (Jamkesmas)	16%	0%	0%
Askes	1%	0%	0%
Out-of-Pocket	2%	2%	1%
BPJS Kesehatan (Total)	0%	55%	65%
BPJS Kesehatan Capitation	0%	52%	62%
BPJS Kesehatan Non-Capitation	0%	2%	3%
BPJS Kesehatan Other	0%	1%	0%
Local Government Budget	20%	18%	14%
Health Operational Aid	35%	19%	16%
Unclassified	0%	0%	1%

Source: World Bank, 2018 analysis based on Quantitative Service Delivery Survey

Table C2. Capitation Criteria for Puskesmas

Number	Capitation Criteria	Maximum Capitation Tariff (IDR)					
	Availability	6,000	5,500	5,000	4,500	3,500	3,000
1	General Practitioner (GP)						
	One GP	No	No	Yes	Yes	No	No
	At least three GP	Yes	Yes	No	No	No	No
2	Dentist	Yes	No	Yes	No	Yes	No
3	Midwife/Nurse	Yes	Yes	Yes	Yes	Yes	Yes
4	Laboratories	Yes	Yes	Yes	Yes	Yes	Yes
5	Pharmacy	Yes	Yes	Yes	Yes	Yes	Yes

Source: (BPJS Kesehatan, 2015a)

Table C3. Illustration of the individual weight calculation based on hypothetical data

Household Category		Households with JKN in a Puskesmas	Subset of sampled households	household weight	Individual weight w_i for each hh member (hh weight/hh size)
1	Non-users	9,771	10	977.1	244.3
2	Primary care users	630	10	63.0	15.7
3	Primary and hospital care users	237	10	23.7	5.9
	Total household	10,638			

Note: utilization between January 1, 2015, and December 31, 2015 for all household members

Illustration of a puskesmas in Indonesia based on hypothetical data. When ten households from Category 2 (primary care users) are sampled from a total of 630 JKN households using primary care services from a specific puskesmas, then each household receives a weight of 63.0. Individual weights are then derived from the household weight through division by this household size, resulting in an individual weight of 15.7. We multiply this individual weight with a JKN member visit record.

Table C4. Result of Coarsened Exact Matching of intervention to control districts

KBK	Not matched	Matched	Total
0 (control)	138	300	438
1 (intervention)	3	27	30
Total	141	327	468

Table C5. Robustness to different coarsened exact matching regimes in CEM weighted two-way fixed effects regression

		(1)	(2)	(3)
		Contact percentage	Chronic disease contact percentage	Non specialistic referral rate
Full Sample (without CEM) KBK=30 non-KBK= 429	KBK Announcement	0.622^{***}	1.157^{***}	-0.744
		(0.0397)	(0.110)	(1.714)
	N	10,438	10,438	9,705
District controls can be different provinces, KBK=27 non-KBK=300	KBK Announcement	0.578^{***}	1.149^{***}	0.101
		(0.0445)	(0.127)	(1.670)
	N	7,810	7,810	7,453
District controls can be different provinces, with only one exact match (k2k) KBK=27 non-KBK=27	KBK Announcement	0.666^{***}	1.266^{***}	-0.299
		(0.0667)	(0.194)	(1.994)
	N	1287	1287	1278
District controls must be in in the same province KBK=13 non-KBK=27	KBK Announcement	0.632^{***}	0.999^{***}	4.049
		(0.0818)	(0.230)	(2.581)
	N	958	958	930
District controls must be in in the same province, with only one exact match (k2k) KBK=13 non-KBK=13	KBK Announcement	0.601^{***}	0.902^{***}	1.946
		(0.0943)	(0.295)	(2.783)
	N	622	622	619

Notes: standard error in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Time and district fixed effects are not presented.

D. Appendix - When the smoke gets in your lungs: short-term effects of Indonesia's 2015 forest fires on health care use

Appendix D1. Geospatial Data Interpolation

We find that our AOD data downloaded from GEE has a large number of missing values (55 percent). This could affect our estimation if these missing are nonrandom. We use nearby districts' AOD values to predict the missing values. The spatial interpolation process that we use creates a imputed value from nearby sample points by creating a surface based on values at isolated sample points (GIS-Resources, 2013). Geospatial interpolation can be used to fill missing values of any spatially based information such as rainfall, fire, dust and pollution with the predicted value. We choose local neighbourhood approach interpolation called Inverse Distance Weighting (IDW). IDW is predicated on the idea that a value at an unsampled point can be roughly estimated as a weighted average of values at points within a specific cut-off distance or from a set number of s of the points (Mitas & Mitasova, 1999). We only interpolate across space and not do this approach across time. We use the following specification to calculate a missing AOD observation in certain site using this estimation:

$$\widehat{AOD_{st}} = \frac{\sum_i \omega_i \; yAOD_{it}}{\sum_i \omega_i} \qquad (1)$$

Where the missing AOD at district s in month t is replaced by a weighted average of the observed AOD values of its neighboring districts denoted with the subscript i at the same month t. $\widehat{AOD_{st}}$ is the imputed value AOD at district s at month t . ω_i is equal to $\frac{1}{d_i(s)^2}$ and $d_i(s)^2$ is the squared of the Euclidean distance between district i and district s (C. C. Chen et al., 2021). We include all districts which are within a 15 km threshold of districts with missing data. The approach provides the highest weights to the closest neighbors in determining the imputed AOD level for the missing district s. To perform IDW interpolation, we use QGIS toolbox available in the software.

To assess the accuracy of our interpolated AOD values, we compared them with some part of observed values to get the residuals. Our approach involved splitting the raw data (neighbouring areas) into 80% for prediction and 20% for validation. We then conducted interpolation using 80% of the data and validated it with the remaining 20%. The difference between these two are the residuals. From these residuals we can calculate error metrics such as root mean squared error (RMSE). A low RMSE indicates that the IDW interpolations are close to the actual values, indicating a better fit of the model to the data and more precise. Conversely, higher RMSE values suggest that the model's predictions are farther from the actual values, indicating more error and less precision in the predictions. We found that our RMSE is 0.133 meaning that our IDW interpolation data is close to the observed value in the validation sample.

References

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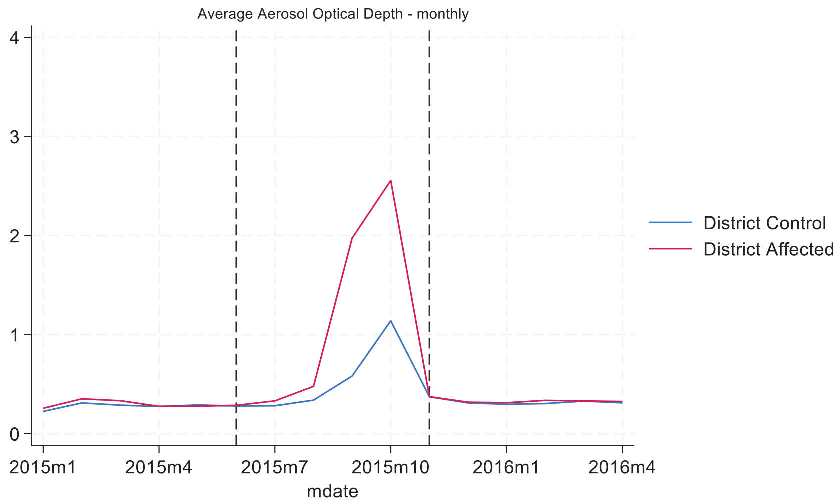
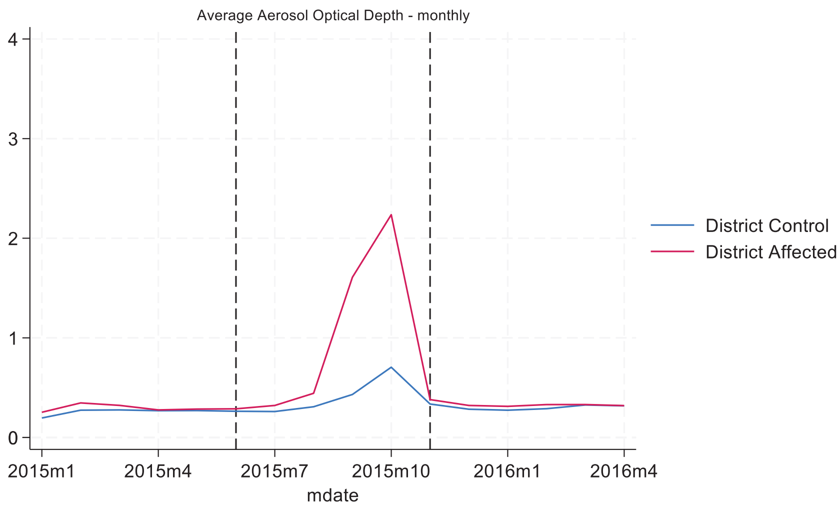
Figure D1. Average AOD Trend in Sumatera and Kalimantan Islands (District Affected vs District Control)

Cut off AOD=0.75



Cut off AOD=0.50



Source: Author analysis based on AOD value from MODIS Data.

Note: District affected is a district with an AOD 5-month average value > 0.75 during forest fire period; District control is a district with an AOD 5-month average value < 0.75 during forest fire period (June to October 2015). We use a threshold of AOD equal to 0.50 for a robustness check and comparison. We find that even with the lower threshold, there is still a small rise in critical AOD visible in the control districts, but less so than with the higher (0.75) threshold. This highlights the fact that any arbitrary threshold will show some spillover effect of the smoke of forest fires in neighbouring districts. The difference between treated and controls, however, remains similar.

Table D1. The Effect of Forest Fire Affected Districts on Primary Care Utilization 2015-2016 (Standard DID)

	Under Five Years Old				Over Five Years Old			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Visit per 1,000 Under Five members	Respiratory visits per 1,000 Under Five members	Common Cold visit per 1,000 Under Five members	ARTI visit per 1,000 Under Five members	Total Visit per 1,000 Over Five members	Respiratory visits per 1,000 Over Five members	Common Cold visit per 1,000 Over Five members	ARTI visit per 1,000 Over Five members
During Forest Fire	3.442*	1.888	1.775	-0.281	0.0793	0.0274	0.0156	0.00586
	(1.821)	(1.402)	(1.204)	(0.331)	(0.370)	(0.0717)	(0.0315)	(0.0370)
After Forest Fire	5.164**	3.889**	3.667**	-0.664*	0.241	0.0644	-0.0537	0.0682*
	(2.213)	(1.744)	(1.518)	(0.370)	(0.365)	(0.0768)	(0.0329)	(0.0395)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	3,216	3,216	3,216	3,216	3,216	3,216	3,216	3,216

Table D2. The Effect of Forest Fire Affected Districts on Hospital Care Utilization 2015-2016 (Standard DID)

	Under Five Years Old				Over Five Years Old			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Visit per 1,000 Under Five members	Respiratory visits per 1,000 Under Five members	Common Cold visit per 1,000 Under Five members	ARTI visit per 1,000 Under Five members	Total Visit per 1,000 Over Five members	Respiratory visits per 1,000 Over Five members	Common Cold visit per 1,000 Over Five members	ARTI visit per 1,000 Over Five members
During Forest Fire	-3.145***	0.138	-0.0511	0.314**	-0.204	0.0777	0.000928	0.00187
	(1.169)	(0.410)	(0.110)	(0.151)	(0.465)	(0.0478)	(0.00666)	(0.00713)
After Forest Fire	-4.990***	0.344	0.220**	0.203	0.258	0.110**	0.00232	0.000321
	(1.255)	(0.392)	(0.109)	(0.160)	(0.479)	(0.0461)	(0.00641)	(0.00752)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y
District Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	3,216	3,216	3,216	3,216	3,216	3,216	3,216	3,216

Standard errors in parentheses * $p<0.10$; ** $p<0.05$; *** $p<0.01$

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

Table D3. The Effect of forest fire affected districts on primary care utilization under five years old (urban vs rural) (Standard DID)

	City + Regency				City (urban)				Regency (rural)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members
During Forest Fire	3.442*	1.888	1.775	-0.281	5.804***	3.401**	2.247***	0.229	3.030	1.645	1.734	-0.384
	(1.821)	(1.402)	(1.204)	(0.331)	(2.020)	(1.387)	(0.657)	(0.842)	(2.256)	(1.749)	(1.526)	(0.357)
After Forest Fire	5.164**	3.889**	3.667**	-0.664*	5.930***	3.028**	1.590**	-0.266	5.259*	4.333**	4.336**	-0.742*
	(2.213)	(1.744)	(1.518)	(0.370)	(2.176)	(1.505)	(0.715)	(0.927)	(2.765)	(2.191)	(1.931)	(0.404)
District Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	3,216	3,216	3,216	3,216	656	656	656	656	2,560	2,560	2,560	2,560

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

Table D4. The Effect of forest fire affected districts on hospital care utilization under five years old (urban vs rural) (Standard DID)

	City + Regency				City (urban)				Regency (rural)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total Visit per 1,000 Under Five Years enrolees	Respiratory visits per 1,000 Under Five Years enrolees	Common Cold visit per 1,000 Under Five Years enrolees	ARTI visit per 1,000 Under Five Years enrolees	Total Visit per 1,000 Under Five Years enrolees	Respiratory visits per 1,000 Under Five Years enrolees	Common Cold visit per 1,000 Under Five Years enrolees	ARTI visit per 1,000 Under Five Years enrolees	Total Visit per 1,000 Under Five Years enrolees	Respiratory visits per 1,000 Under Five Years enrolees	Common Cold visit per 1,000 Under Five Years enrolees	ARTI visit per 1,000 Under Five Years enrolees
During Forest Fire	-3.145***	0.138	-0.0511	0.314**	-3.489	0.595	0.164	0.176	-3.090***	0.0371	-0.109	0.352**
	(1.169)	(0.410)	(0.110)	(0.151)	(3.419)	(0.760)	(0.183)	(0.286)	(1.188)	(0.473)	(0.129)	(0.174)
After Forest Fire	-4.990***	0.344	0.220**	0.203	-6.981*	-1.586**	-0.119	-0.651**	-4.962***	0.793*	0.294**	0.407**
	(1.255)	(0.392)	(0.109)	(0.160)	(3.940)	(0.746)	(0.174)	(0.320)	(1.225)	(0.451)	(0.128)	(0.183)
District Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	3,216	3,216	3,216	3,216	656	656	656	656	2,560	2,560	2,560	2,560

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

Table D5. The Effect of forest fire affected districts on primary care utilization <u>over five years old</u> (urban vs rural) (ANCOVA Regression)

	City + Regency				City (urban)				Regency (rural)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members
During Forest Fire	0.160	0.0312	-0.0135	0.00239	1.756***	0.690***	0.0927	0.197***	-0.0168	-0.0709	-0.0298	-0.0220
	(0.259)	(0.0606)	(0.0258)	(0.0295)	(0.481)	(0.170)	(0.0665)	(0.0757)	(0.298)	(0.0603)	(0.0266)	(0.0295)
After Forest Fire	0.312	0.0679	-0.0845***	0.0661	4.046***	1.036***	0.0469	0.284***	-0.351	-0.104	-0.106***	0.0413
	(0.347)	(0.0822)	(0.0290)	(0.0447)	(0.768)	(0.212)	(0.0757)	(0.0901)	(0.340)	(0.0820)	(0.0307)	(0.0498)
Pre-Fire Outcome (January-May 2015)	1.032***	0.957***	0.751***	1.053***	0.890***	0.896***	0.669***	1.005***	1.163***	1.192***	0.927***	1.285***
	(0.0703)	(0.0249)	(0.0254)	(0.0325)	(0.0275)	(0.0303)	(0.0317)	(0.0412)	(0.128)	(0.0379)	(0.0375)	(0.0416)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	2,203	2,203	2,203	2,203	451	451	451	451	1,752	1,752	1,752	1,752

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

Table D6. The Effect of forest fire affected districts on hospital care utilization <u>over five years</u> old (urban vs rural) (ANCOVA Regression)

	City + Regency				City (urban)				Regency (rural)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members	Total Visit per 1,000 Under Five Years JKN members	Respiratory visits per 1,000 Under Five Years JKN members	Common Cold visit per 1,000 Under Five JKN Years members	ARTI visit per 1,000 Under Five Years JKN members
During Forest Fire	-0.200	0.00542	-0.00289	0.00213	3.210**	0.102	-0.00306	0.0146	-1.245***	-0.0240	-0.00343	0.00152
	(0.396)	(0.0343)	(0.00301)	(0.00555)	(1.312)	(0.0985)	(0.00424)	(0.0131)	(0.353)	(0.0376)	(0.00367)	(0.00643)
After Forest Fire	0.235	0.0377	-0.00145	0.000518	5.211***	-0.0687	-0.00320	-0.0231**	-1.578***	0.0523	-0.00197	0.00905
	(0.454)	(0.0394)	(0.00257)	(0.00630)	(1.455)	(0.113)	(0.00634)	(0.0105)	(0.417)	(0.0391)	(0.00283)	(0.00798)
Pre-Fire Outcome (January-May 2015)	1.032***	0.737***	0.495***	0.853***	0.990***	0.697***	0.762***	0.559***	0.946***	0.743***	0.487***	0.952***
	(0.0125)	(0.0253)	(0.0579)	(0.108)	(0.0174)	(0.0327)	(0.0683)	(0.0421)	(0.0223)	(0.0479)	(0.0595)	(0.145)
Time Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N: District-Month	2,203	2,203	2,203	2,203	451	451	451	451	1,752	1,752	1,752	1,752

Standard errors in parentheses * p<0.10; ** p<0.05; *** p<0.01

Note: District JKN Member use January 2015 JKN member per district figure as a baseline.

Table D7. Robustness Test for ANCOVA with Different AOD Threshold

Primary Care Service

		Under Five Years Old				Over Five Years Old			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Total Visit per 1,000 Under Five members	Respiratory visits per 1,000 Under Five members	Common Cold visit per 1,000 Under Five members	ARTI visit per 1,000 Under Five members	Total Visit per 1,000 Over Five members	Respiratory visits per 1,000 Over Five members	Common Cold visit per 1,000 Over Five members	ARTI visit per 1,000 Over Five members
Threshold: 0.50	During Forest Fire	5.937**	2.876*	1.435	0.852***	0.614*	0.154*	-0.110**	0.111***
Treated=184; Control=36		(2.328)	(1.571)	(0.970)	(0.213)	(0.314)	(0.0848)	(0.0458)	(0.0239)
	After Forest Fire	7.667***	5.123***	3.182***	0.650	1.327***	0.283**	-0.107**	0.134***
		(2.488)	(1.775)	(1.085)	(0.409)	(0.449)	(0.112)	(0.0434)	(0.0448)
Threshold: 0.75	During Forest Fire	1.421	0.432	0.264	-0.277	0.160	0.0312	-0.0135	0.00239
Treated= 89; Control=131		(1.408)	(1.089)	(0.791)	(0.269)	(0.259)	(0.0606)	(0.0258)	(0.0295)
	After Forest Fire	3.130*	2.406*	2.136***	-0.655	0.312	0.0679	-0.0845***	0.0661
		(1.634)	(1.251)	(0.801)	(0.406)	(0.347)	(0.0822)	(0.0290)	(0.0447)

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Pre-fire outcome is not shown because do not change much. we use time dummies. N: District-Month equals to 2,203.

Table D8. Robustness Test for ANCOVA with Different AOD Threshold

Hospital Care Service

		Under Five Years Old				Over Five Years Old			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Total Visit per 1,000 Under Five members	Respiratory visits per 1,000 Under Five members	Common Cold visit per 1,000 Under Five members	ARTI visit per 1,000 Under Five members	Total Visit per 1,000 Over Five members	Respiratory visits per 1,000 Over Five members	Common Cold visit per 1,000 Over Five members	ARTI visit per 1,000 Over Five members
Threshold: 0.50	During Forest Fire	-5.175***	-2.024***	-0.262*	-0.291	-0.512	-0.0963	-0.0123**	-0.0140
Treated=184; Control=36		(1.571)	(0.630)	(0.157)	(0.200)	(0.604)	(0.0632)	(0.00581)	(0.0100)
	After Forest Fire	-7.209***	-1.791***	0.113	-0.297	-1.029	0.00302	-0.00677	-0.000142
		(1.697)	(0.535)	(0.128)	(0.222)	(0.653)	(0.0655)	(0.00438)	(0.00975)
Threshold: 0.75	During Forest Fire	-3.261***	-0.275	-0.132	0.170	-0.200	0.00542	-0.00289	0.00213
Treated= 89; Control=131		(0.951)	(0.318)	(0.0812)	(0.105)	(0.396)	(0.0343)	(0.00301)	(0.00555)
	After Forest Fire	-5.147***	-0.0767	0.141*	0.0606	0.235	0.0377	-0.00145	0.000518
		(1.244)	(0.298)	(0.0791)	(0.127)	(0.454)	(0.0394)	(0.00257)	(0.00630)

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Pre-fire outcome is not shown because do not change much. We use time dummies. N: District-Month equals to 2,203.

Generally, examining the robustness strengthens rather than weakens our results. For instance, comparing two cutoff applications (0.50 vs 0.75), we observe that all primary care visits in children under five years old during the fire period yield estimates four times larger (5.94 vs 1,42) and twofold higher after the fire (7.67 vs 3.13). Similarly, respiratory disease and ARTI visits also show higher effect estimates during and after the forest fire. This pattern is also evident in individuals over five years old, where initially nonsignificant estimates become significant. The estimates for hospital care are now significant but lower compared to those for primary care services for the under five years age group, with greater forgone care in hospital services during (-3.26 vs -5.18) and after the forest fire (-5.15 vs -7.21). Furthermore, we now find significant negative effects for visits to the hospital for respiratory diseases (-2.02) and common colds (-0.26) in the same age group. The changes in estimates after introducing a lower cutoff are less apparent in hospital care visits for individuals over five years old, with only common cold visits showing a significant negative effect (-0.012).

Table D9. Ordinary Least Square Regression with forest fire affected status, month dummies, and interaction of time dummies and treatment status (Primary Care)

	(1) Total Visit per 1,000 Under Five members	(2) Respiratory visits per 1,000 Under Five members	(3) Common Cold visit per 1,000 Under Five members	(4) ARTI visit per 1,000 Under Five members	(5) Total Visit per 1,000 Over Five members	(6) Respiratory visits per 1,000 Over Five members	(7) Common Cold visit per 1,000 Over Five members	(8) ARTI visit per 1,000 Over Five members
Affected Districts (1=Yes; 0=No)	1.047	0.628	0.251	0.512	-1.671	-0.0199	-0.126	0.114
	(6.535)	(3.891)	(3.539)	(0.997)	(1.398)	(0.310)	(0.114)	(0.135)
February 2015	1.142	0.911	0.0901	0.593	-0.346	0.0533	0.00156	0.0111
	(7.117)	(4.238)	(3.854)	(1.086)	(1.523)	(0.337)	(0.124)	(0.147)
March 2015	3.881	2.982	1.150	1.394	-0.601	0.246	0.0743	0.0936
	(7.161)	(4.264)	(3.878)	(1.092)	(1.533)	(0.339)	(0.125)	(0.147)
April 2015	4.053	2.574	0.967	1.234	-0.387	0.184	0.0294	0.0487
	(7.161)	(4.264)	(3.878)	(1.092)	(1.533)	(0.339)	(0.125)	(0.147)
May 2015	2.839	1.784	0.484	1.151	0.623	0.163	-0.00378	0.0657
	(7.139)	(4.251)	(3.866)	(1.089)	(1.528)	(0.338)	(0.125)	(0.147)
June 2015	2.824	1.698	0.0920	1.213	-0.310	0.156	-0.0272	0.0757
	(7.139)	(4.251)	(3.866)	(1.089)	(1.528)	(0.338)	(0.125)	(0.147)
1.Affected#February 2015	1.511	1.935	2.022	-0.185	0.545	-0.0228	0.0115	-0.0237
	(9.241)	(5.502)	(5.004)	(1.410)	(1.978)	(0.438)	(0.161)	(0.190)
1.Affected#March 2015	2.163	0.424	0.886	-0.746	1.877	-0.120	-0.0323	-0.0730
	(9.283)	(5.527)	(5.027)	(1.416)	(1.987)	(0.440)	(0.162)	(0.191)
1.Affected#April 2015	3.039	1.561	1.998	-0.878	1.779	-0.104	-0.0436	-0.0392
	(9.283)	(5.527)	(5.027)	(1.416)	(1.987)	(0.440)	(0.162)	(0.191)
1.Affected#May 2015	1.389	1.626	2.046	-0.801	-0.136	-0.174	-0.0115	-0.0900
	(9.258)	(5.512)	(5.013)	(1.412)	(1.981)	(0.439)	(0.162)	(0.191)
1.Affected#June 2015	4.671	2.071	2.731	-0.818	1.187	-0.131	0.0256	-0.0860
	(9.266)	(5.517)	(5.018)	(1.413)	(1.983)	(0.439)	(0.162)	(0.191)
Constant	13.56***	7.537**	2.799	2.460***	7.044***	1.334***	0.465***	0.363***
	(5.033)	(2.996)	(2.725)	(0.768)	(1.077)	(0.238)	(0.0878)	(0.104)
N	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215

Table D10. Ordinary Least Square Regression with forest fire affected status, month dummies, and interaction of time dummies and treatment status (Hospital Care)

	(1) Total Visit per 1,000 Under Five members	(2) Respiratory visits per 1,000 Under Five members	(3) Common Cold visit per 1,000 Under Five members	(4) ARTI visit per 1,000 Under Five members	(5) Total Visit per 1,000 Over Five members	(6) Respiratory visits per 1,000 Over Five members	(7) Common Cold visit per 1,000 Over Five members	(8) ARTI visit per 1,000 Over Five members
Affected District (1=Yes; 0=No)	-1.621	-1.171	-0.00576	-0.328	1.208	-0.166	-0.0202	0.00575
	(4.987)	(1.135)	(0.285)	(0.386)	(3.910)	(0.232)	(0.0176)	(0.0212)
February 2015	1.630	1.173	0.145	0.223	-0.249	0.0455	-0.0144	0.0212
	(5.432)	(1.237)	(0.311)	(0.420)	(4.259)	(0.253)	(0.0191)	(0.0231)
March 2015	12.31**	3.207**	0.262	0.324	4.292	0.205	-0.0155	-0.00122
	(5.465)	(1.244)	(0.313)	(0.423)	(4.285)	(0.254)	(0.0192)	(0.0233)
April 2015	9.094*	1.838	0.174	-0.123	4.272	0.115	-0.0130	-0.0179
	(5.465)	(1.244)	(0.313)	(0.423)	(4.285)	(0.254)	(0.0192)	(0.0233)
May 2015	6.950	1.058	0.165	-0.257	1.899	-0.0149	-0.0221	-0.0171
	(5.448)	(1.240)	(0.312)	(0.422)	(4.272)	(0.253)	(0.0192)	(0.0232)
June 2015	6.942	-0.0207	0.102	-0.841**	2.309	-0.0805	-0.0226	-0.0307
	(5.448)	(1.240)	(0.312)	(0.422)	(4.272)	(0.253)	(0.0192)	(0.0232)
1.Affected#February 2015	-0.906	-0.836	-0.183	-0.181	-0.0107	0.0122	0.0336	-0.0121
	(7.053)	(1.606)	(0.403)	(0.546)	(5.530)	(0.328)	(0.0248)	(0.0300)
1.Affected#March 2015	-6.149	-1.567	-0.328	-0.108	-1.966	-0.212	0.0147	-0.00185
	(7.084)	(1.613)	(0.405)	(0.548)	(5.555)	(0.329)	(0.0249)	(0.0302)
1.Affected#April 2015	-5.028	-1.524	-0.333	0.0244	-2.720	-0.191	0.00285	-0.00629
	(7.084)	(1.613)	(0.405)	(0.548)	(5.555)	(0.329)	(0.0249)	(0.0302)
1.Affected#May 2015	-5.307	-2.130	-0.476	-0.233	-1.643	-0.135	0.0132	0.000921
	(7.065)	(1.609)	(0.404)	(0.547)	(5.540)	(0.328)	(0.0249)	(0.0301)
1.Affected#June 2015	-4.668	-1.068	-0.355	0.299	-0.994	-0.105	0.0103	-0.00156
	(7.071)	(1.610)	(0.405)	(0.547)	(5.545)	(0.329)	(0.0249)	(0.0301)
Constant	32.08***	6.959***	0.819***	2.125***	20.53***	1.091***	0.0494***	0.0880***
	(3.841)	(0.874)	(0.220)	(0.297)	(3.012)	(0.179)	(0.0135)	(0.0163)
N	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215

Table D11. F-Test Report using Ordinary Least Square Regression with time, forest fire affected status, and interaction of time dummies and treatment status (Primary Care and Hospital Care)

Type of Facility	Age Group	Outcome	January-June 2015 (6 month) Interaction of time dummies and district treatment status	Reject Ho or Not
Primary Care	Under Five Years Old	All Visits	Prob > F = 0.9977	No
		Respiratory Disease	Prob > F = 0.9986	No
		Common Cold	Prob > F = 0.9956	No
		ARTI	Prob > F = 0.9821	No
	Over Five Years Old	All Visits	Prob > F = 0.8588	No
		Respiratory Disease	Prob > F = 0.9987	No
		Common Cold	Prob > F = 0.9983	No
		ARTI	Prob > F = 0.9961	No
Hospital Care	Under Five Years Old	All Visits	Prob > F = 0.9337	No
		Respiratory Disease	Prob > F = 0.8377	No
		Common Cold	Prob > F = 0.8916	No
		ARTI	Prob > F = 0.9437	No
	Over Five Years Old	All Visits	Prob > F = 0.9956	No
		Respiratory Disease	Prob > F = 0.9756	No
		Common Cold	Prob > F = 0.8079	No
		ARTI	Prob > F = 0.9982	No

Note: Number of district-month observations are 1,215

List of Publications

Article in this PhD project

1. Sambodo NP Van Doorslaer E Pradhan M Sparrow R, 2021, *Does geographic spending variation exacerbate healthcare benefit inequality? A benefit incidence analysis for Indonesia*. Health Policy and Planning, 36 (7), 1129-1139 - doi: 10.1093/heapol/czab015.
2. Sambodo NP, Bonfrer I, Sparrow R, Pradhan M, van Doorslaer E. *Effects of performance-based capitation payment on the use of public primary health care services in Indonesia*. Social Science and Medicine, 327 - doi: 10.1016/j.socscimed.2023.115921.

Articles in other projects

3. Sambodo, NP, 2018, *The Impact Of Jamkesmas On Healthcare Utilization In Eastern Regions Of Indonesia: A Propensity Score Matching Method*, Jurnal Ekonomi & Studi Pembangunan, 19(2). https://doi.org/10.18196/jesp.19.2.5003
4. Wibowo RA, Hartarto RB, Bhattacharjee A, Wardani DTK, Sambodo NP, Santoso Utomo P, Annisa L, Hakim MS, Sofyana M and Dewi FST, 2023, *Facilitators and barriers of preventive behaviors against COVID-19 during Ramadan: A phenomenology of Indonesian adults*. Front. Public Health 11:960500. doi: 10.3389/fpubh.2023.960500

Policy Brief

5. Baiq L. S. W. Wardhani, Vinsensio M. A. Dugis, Hennida C, Dharmaputra R, Wardhana A, Santoso YW, Nauvarian D, Sugianto MA, Sambodo NP, Nugraha RR, Sayekti M, Oktamianti P, *G20 As A Hub For Multilevel Governance In A Pandemic Responses*, T20 Communique, link: <https://summit.t20indonesia.org/wp-content/uploads/2022/09/T20-Communique%CC%81.pdf>.

PhD Portofolio

Courses

Description	Organizer	EC
Mixed method research: How to combine diverse quantitative and qualitative methods	EGSH - Erasmus Graduate School of Social Sciences and the Humanities	2.50
Data visualisation, web scraping, and text analysis in R	EGSH - Erasmus Graduate School of Social Sciences and the Humanities	2.50
Brush up your SPSS skills	EGSH - Erasmus Graduate School of Social Sciences and the Humanities	1.00
Shut up and write	EGSH - Erasmus Graduate School of Social Sciences and the Humanities	1.00
How to get your article published	EGSH - Erasmus Graduate School of Social Sciences and the Humanities	2.50
Self-presentation: focus, structure, interaction and visualisation	EGSH - Erasmus Graduate School of Social Sciences and the Humanities	2.50
Analytic storytelling	Eramus Graduate School of Social Sciences and the Humanities	2.50
Data analysis with R	Eramus Graduate School of Social Sciences and the Humanities	1.00
Doing the literature review	Eramus Graduate School of Social Sciences and the Humanities	1.00
Philosophy of the social sciences and humanities	Eramus Graduate School of Social Sciences and the Humanities	2.50
Economics of Health Inequality	Tinbergen Institute Summer Schoo	3.00
English academic writing for PhD candidates	Eramus Graduate School of Social Sciences and the Humanities	2.50
Professionalism and integrity in research	Eramus Graduate School of Social Sciences and the Humanities	1.00
How to Survive your PhD	EGSH - Erasmus Graduate School of Social Sciences and the Humanities	2.50
Applied Microeconometrics II	Tinbergen Institute	3.00
Total ECTS		**31.00**

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As the Arabic phrase goes ‘man jadda wajada’ — “whoever strives shall succeed.”

About the Author

Novat Pugo Sambodo, born on November 4th, 1986, in Bantul, Yogyakarta, Indonesia. He has resided in Yogyakarta for the majority of his life, where he pursued a Bachelor's degree in Economics from Universitas Gadjah Mada in 2010. His journey beyond Yogyakarta commenced with roles in the Indonesian Vice President's Office and the National Team for the Acceleration of Poverty Reduction (TNP2K) in Jakarta, Indonesia. Following this, he undertook a Master's degree in International and Development Economics at the Australian National University, graduating in 2015. Upon his return to Indonesia, he participated in the NUFFIC Project on Strengthening Capacity In Health Insurance and Finance, a collaboration between the Center for Health Financing Policy and Health Insurance Management (Pusat KPMAK) Medical Faculty at Universitas Gadjah Mada and Dutch Universities/Institutions. This endeavor ultimately paved the way for his doctoral studies at the Erasmus School of Health Policy and Management (ESHPM) at Erasmus University Rotterdam in the Netherlands.

Embarking on his PhD in 2016, he secured funding from the Indonesian Endowment Fund for Education (LPDP) by the Indonesian Government. His research at ESHPM revolves around evaluating health equity and healthcare financing in light of Indonesia's Universal Health Coverage implementation. Specializing in healthcare equity and policy evaluation, his endeavors have fostered collaborations with prominent stakeholders in the Indonesian health sector, including BPJS-Kesehatan, USAID, the G20 Health Sector committee, and academic partners such as Heriot-Watt University in the United Kingdom.

Pugo is currently a lecturer at the Department of Economics at Universitas Gadjah Mada, Indonesia. He teaches Introduction to Economics and Health Economics at the undergraduate level and Statistics at the postgraduate level. Additionally, he serves as the coordinator of the Center for Islamic Economics and Business Studies working group within his department. After completing his Ph.D. studies, Pugo is passionate about developing and teaching health economics studies at the Faculty of Economics and Business, Universitas Gadjah Mada, and beyond in academic and non-academic settings.

For more information about Pugo and his work, visit his website at www.acadstaff.ugm.ac.id/novatpugosambodo or connect with him on Twitter/X @pugosambodo.