

Estimating Informal-Economy Gross Value Added for Bengaluru, 2025–26

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ABSTRACT

This paper estimates the informal-economy Gross Value Added (GVA) for Bengaluru during the Fiscal Year 2025–26 through a bottom-up income approach. While India's informal economy constitutes the majority of its workforce, it remains unrepresented in official output data, with no data available for individual cities. A total of 85 individual worker records and 326 cohort-level observations were collected through field surveys in Whitefield, which is a sub-region in eastern Bengaluru known for its dense informal economy in close proximity to a large formal economy information-technology sector. Wages observed in the field were incorporated along with benchmarks into estimates that aggregate 13 worker categories to arrive at informal-economy GVA via value-added multipliers from the NSS 73rd Round enterprise survey. These estimates were extrapolated to the size of the entire informal economy using a coverage factor made up of six independent measures.

According to the eleven worker categories that are the most reliably estimated based on primary field data, the GVA of the informal economy in Bengaluru would be ₹1,84,844 crore, i.e., 15.1% of Bengaluru city GDP (coverage range ₹1,51,808–₹2,21,025 crore; 12.4–18.0%). Including the two imputed household-services categories raises the GVA estimate to ₹1,97,022 crore (16.0%). The total range of possible values, according to different assumptions, is ₹1,34,650–₹2,86,182 crore (11.0–23.3%), while the uncertainty envelope is ₹1,47,766–₹2,46,277 crore (12.0–20.1%). The estimated number is below the often-cited benchmark of the informal share of the national urban economy of 45%, a discrepancy that can be attributed to the income-approach methodology, which includes only worker-linked value, and also to the highly productive formal sector in Bengaluru, which decreases the formal share of output despite having a majority of its workforce constituted by informal workers. All input data directly comparable to published sources have been accounted for.

1. INTRODUCTION

1.1 The measurement problem

Most of the workers in India work in areas beyond the ambit of official regulation, as they do not have

written contracts or legal entitlements and are not formally recorded in payrolls and tax data. According to the Periodic Labour Force Survey of July 2023 to June 2024, the trend of expansion of the urban labour force continues with predominance of informal engagement. In the entire developing world, according to the ILO, the share of the informal sector and informal employment in total employment, excluding agriculture, ranges from half to three-fourths (International Labour Organization, 2025). Output data reflect only part of this activity. National accounts are compiled based on surveys of firms, accounting and tax reports, and hence incorporate informal production indirectly. For an individual city, the gap is even bigger, as there is no statutory body that provides city GDP for Bengaluru or any detailed information about the contribution of the informal workers of the city by categories.

1.2 Three approaches to GDP, and the basis for this study

The GDP is calculated using three types of national accounting methods, namely, the output method (or expenditure method), where the total value of the goods and services produced is measured (Office for National Statistics, n.d.), the income method, where incomes from factors like wages, profit and rents are aggregated; and the production method, which is used to aggregate value-added from producing units. This research employs the income method as it originates from an observable and auditable unit (the wage income of an individual worker). In this study, the income approach is used and built up from granular observations. The justification lies in the alignment with the purpose of the work. A sub-national government needs a measure that can be audited, attributed to specific worker groups, and updated in case new data become available. The income approach starts with an observable variable – worker incomes – and a bottom-up strategy, which allows tracing all intermediate steps from surveyed wages to the overall number. The income approach is based on labour input and mixed surveys described in the ILO manual. It follows the enterprise survey approach used by NSSO in its 73rd Round, which surveyed value added and wages of 111.3 million workers employed in unincorporated non-agricultural enterprises except construction (Press Information Bureau, n.d.). Now, this quinquennial series is updated annually with ASUSE of MoSPI, where Round 2023-24 was just published.

1.3 Controversy surrounding the extent of the informal economy

The benchmark figure against which informal-GDP estimates are compared is itself controversial. The figures provided by NITI Aayog and NCAER suggest the extent of the informal sector of India's GDP lies between 45 and 50% (NITI Aayog, 2026; National Council of Applied Economic Research, n.d.). For India, the estimates for the informal sector produced using macroeconometric shadow-economy approaches are lower, standing at roughly one-fifth of GDP and on a declining trend over the period under consideration. SBI Research, in November 2021, estimated the post-2017 formalization to have brought down the informal share to 15-20% of gross value added, falling from 52.4% in FY 2017-18 and 53.9% in 2011-12, citing the introduction of the Goods and Services Tax, digitization, and platform work (SBI Research, 2021). Critics pointed out both the levels and the speed of change, arguing the informal sector's pre-pandemic share was more likely 42-44%. There is no uncontroversial figure; the benchmark itself is a wide band of values dependent on definition and methodology. This question is considered again in

Section 4, as it will affect the judgment of the city-level estimates.

1.4 Contribution and objective

It is rare to find city-specific estimates of informal GDP based on income approach surveys in Indian literature, where macro-aggregates and proxies dominate the scene. The aim of this work is not to establish a definitive number for Bengaluru; neither the data nor the study would lend itself to such a claim. The goal is to propose a rigorous, reproducible, extendable method that will generate a credible central estimate with an explicitly stated range of uncertainty and can be further developed by any government department or academic institution. The data and methodology are explained in Section 2, the results are presented in Section 3, while the analysis comparing the findings with other published benchmarks is provided in Section 4.

2. DATA AND METHODOLOGY

2.1 Research design and scope

The research is based on a bottom-up income approach, carried out in two progressively scaled steps. The first step consists of collecting earnings of the informal workers by means of a field survey, combining these with published benchmarks of wages and aggregating them according to worker categories, thus producing a labor income estimate. At the second step, the labor income is transformed into Gross Value Added (GVA) with the help of category-specific value added multipliers, and then these categories are scaled up to cover the whole of the informal economy via a sector coverage factor. The reference period is fiscal year 2025-26 (April 1st, 2025 - March 31st, 2026). Wages collected during the reference year (see §2.2) are used nominally as they are recorded; inter-year deflation is not applied.

The model takes into account thirteen categories of informal workers, chosen according to their relevance in Bengaluru, accessibility for field survey and availability of published benchmarks of wages for validation purposes. These are: Street Vendor/Hawker, Domestic Cook, Domestic Cleaner/Maid, Domestic Driver, Gardener, Construction (Unskilled), Construction (Skilled), Sanitation Worker, Gig/Delivery Worker, Small Shop Owner/Shop Helper, Home-Based Worker, Caregiver/Crèche Worker, and Security Guards. Eleven categories provide primary field data. Two categories, namely home-based workers and crèche caregivers, were not surveyed and are imputed via analogous categories. They are explicitly marked in all results and reported separately; the headline result in Section 3 does not include them. Other categories are not measured individually and enter as a residual part via the coverage factor (Section 2.7).

2.2 Study Area, Sample, and Consent

Whitefield was chosen as the primary area of survey since the economy there consists of formal IT campuses alongside a large amount of informal residential and commercial activities. As a result, the

composition of the labor force in that area, made up of domestic workers, construction workers, gig riders, security guards, vendors, small shop employees, and others, mirrors that of the city. Survey areas included ITPL, Varthur, Brookefield, Hope Farm, Kadugodi, Nallurahalli, Hoodi, and other nearby regions.

Two samples were created. The individual worker sample of Whitefield includes 85 worker profiles with information on sub-area, category, daily wage observed, number of working days, and monthly and annual incomes calculated, collected between 19 February and 7 March 2026. The cohort file includes 326 worker observations collected at the group level in April 2025, including a 53-guard security cohort at an ITPL technology park, three construction cohorts, landscapers' cohorts in residential complexes, and a gig-workers' cohort. Thus, those two files give us 411 worker observations for the Whitefield base zone. Both surveys were held in FY 2025-26, the reference year of our study; wages are quoted in nominal terms as observed, without deflation over years. The individual survey gives us the basis for wages, whereas the number of workers comes from secondary sources; category-specific data are in Appendix D.

Informed consent and data protection were guaranteed throughout the whole process. Consent for participation was secured orally in the course of the interview; no written consent was obtained. It is stated unequivocally. All personal data, including names of people surveyed, their employers' names, and other direct identifying information obtained in fieldwork, have been stripped from this report and from any dataset attached; respondents are identified only by their category and sub-area. Future waves of surveys should employ the written consent format and data protection mechanism to meet archival deposit requirements.

2.3 Wage blending

For each category, the model blends together the observed survey wages and the published benchmark wage, giving higher weight to the survey as the number of observations increases. There are four bands of sample size: 70% survey wages and 30% benchmark wages for samples of ten or more; 40% survey wages and 60% benchmark wages for samples of five to nine; 20% survey wages and 80% benchmark wages for samples of one to four; and 0% survey wages and 100% benchmark wages for samples of zero. The purpose is to keep the estimate data-driven, such that field observations will progressively crowd out assumptions as they accumulate. The cut-offs are arbitrary tuning parameters rather than statistically determined weights. A better method would use an inverse-variance (Bayesian) blend, which would require surveying individuals' wages and recording their variability, something that is recommended for future waves (Section 5.4).

This scheme follows the typical composite estimation approach used in small-area statistics, where a direct sample estimate is smoothed toward a more reliable external benchmark when the sample size is small, with the sample's weight increasing with sample size. The particular thresholds correspond to the points where random fluctuations due to sampling are presumed to be overwhelming: for one to four observations, an individual response in the form of an outlier, like those shop-owners in the individual wage data set, can affect the mean of a category significantly; thus, the survey is considered to be

informative yet secondary compared to the benchmark (20%). Five to nine observations make it possible to see the shape of a variable's distribution, yet the sample standard error is still relatively high compared to an institutional benchmark, so almost equal weights are assigned, again in favor of the benchmark (40%). For ten or more observations, the sample mean of a category is supposed to be stable for a bounded and somewhat skewed variable like daily wage; thus, the survey is assigned the main weight (70%) while the benchmark still has some minimum weight because all field data have been collected in a very short time in one sub-region and even the largest categories fall well short of a full population sample

2.4 Number of workers and category structure

Worker numbers in Bengaluru by category come from specific-sector sources: KBOCWFB and Karnataka Labour Department figures for construction (Karnataka Building and Other Construction Workers Welfare Board, 2025); Fairwork India for gig workers (Fairwork, 2024); BBMP and Hasiru Dala for sanitation (Bruhat Bengaluru Mahanagara Palike, 2024; Dala, n.d.); Private Security Agencies (Regulation) Act license registration for security services; agencies and welfare trust data for domestic workers; HomeNet India for home-based and care work (HomeNet India & SEWA, 2024). Every category has a data-quality tier (High, Medium, Low) coded into the model and listed in Appendix A. Categories in the high tier used government official data, statutory records or peer-reviewed research studies as sources; those in the medium tier used reliable institutional/industry sources that required only limited estimation; and those in the lowest tier used commercial or survey sources that had limited verification. The two largest categories in aggregate, construction and gig workers, have the best sources; the worst source, residential associations for gardeners, is attached to a low-weight category (about 2% of category GVA).

2.5 Imputation for zero-sample categories

There were two zero-sample categories: home-based workers and caregivers. Rather than dropping them, which would downplay the size of the informal economy, and rather than applying the national benchmark without regard for local conditions, both of these categories were imputed from their closest local analogues, scaled by an adjustment factor based on overlap of their incomes. In the case of home-based workers, the local analogue was domestic cleaners with a factor of 0.92, representing the piece-rate discount on intermittent work. Crèche caregivers were imputed from domestic cooks with a factor of 0.91, reflecting the discount on caregivers' wages in the Bengaluru household services market. The resulting imputed wages were ₹7,820 and ₹9,555 per month. Each was within 5% of their independently published benchmarks (HomeNet India), falling within the $\pm 15\%$ tolerance level above which the benchmark is not used. These categories are designated as 'imputed' in all the output; Section 3.1 shows a sensitivity analysis excluding them, and the headline figures omit them.

2.6 Value-added multipliers

The wage rate is lower than value added. This is because the compensation of a worker does not include the remuneration for the non-labour inputs that were used to generate the income, including stock, machinery and business overheads. This gap is usually corrected using a multiplier of the ratio of labour income to the wage share of the value added. The wage share of value added is found to be roughly 40% in the informal sector from the NSS 73rd Round enterprise surveys, which means the overall multiplier is about 2.54.

Using a single multiplier to each category is the main drawback of the conventional approach, and this research deviates from the approach. Using a 2.5 multiplier is incorrect for those categories that have different characteristics from the 2015-16 average. The most striking example is gig work through platforms, which did not exist in 2015-16: the platform fee of 20 to 30% is the formal sector value added that does not reach the worker, and therefore multiplying 2.5 to the income of a rider includes value that has already been counted in the formal economy (Fairwork, 2024). This is why this model uses multipliers for each of the categories based on the two-digit NIC of the NSS 73rd Round enterprise survey, from 1.30 for gig and security work, with minimum capital, to 2.70 for skilled construction, with long contractor chains and enterprise surplus. The weighted average is 1.82. The 2.5 multiplier is kept as the comparison point in the output so that the results could be compared with other literature; it is not the main estimation. The multipliers should be updated in accordance with the ASUSE 2023-24 (Ministry of Statistics and Programme Implementation, n.d.).

The two-digit NIC categories are not one-to-one correspondents with the thirteen worker categories used here; therefore, each one of the worker categories in this study was reclassified by NIC industry to which it most closely approximates (e.g., street vending to retail trade, and the two construction categories to the construction division). This mapping represents a judgment call and is the second most important judgmental assumption in the model, after coverage factor explained below.

2.7 The Sector-Coverage Factor

Thirteen categories of workers do not cover the complete informal sector. These include informal manufacturing, surplus of the shop owners in addition to their helpers, own-account workers like plumbers and tutors, construction-contractor margin other than the wage component, and informal finance intermediation. To extrapolate from the captured categories to the complete sector, coverage factor needs to be considered.

Earlier versions of this model set the factor at 2.8 by calibrating it to reproduce the 45% benchmark. This approach was circular and did not provide any independent verification. The present version of the model does not involve any calibration process. Instead, the sector coverage factor has been produced from six components obtained independently, each one as a ratio of informal GDP and including: NSS enterprise distribution of the 73rd round, PLFS ratio of own-account workers, construction margin estimates, and RBI & NABARD indicators for informal finance. The individual components are listed in Table 1. Combined with the captured base, the components provide for the midpoint factor of 2.35, with the documented range of 1.93 to 2.81. The benchmark comparison in Section 4 serves only to verify the

output.

Table 1. Decomposition of the sector-coverage factor.

Coverage component (uncaptured informal value)	Share of informal GDP	Low	Mid	High
Informal manufacturing (garment, food, furniture units)	10–15%	0.30	0.40	0.50
Trade enterprise surplus (owner profit above wage helper)	8–12%	0.20	0.28	0.38
Own-account professionals (plumbers, electricians, tutors)	6–10%	0.18	0.25	0.32
Construction-contractor margins above captured wages	5–8%	0.12	0.20	0.28
Informal financial intermediation (chit funds, lenders)	2–4%	0.05	0.10	0.15
Residual own-account workers outside the 13 categories	3–5%	0.08	0.12	0.18
Captured base (the 13 surveyed categories)		1.00	1.00	1.00
Total coverage factor		1.93	2.35	2.81

Table 1. Decomposition of the sector-coverage factor. Component shares are sourced to the NSS 73rd Round enterprise distribution⁴, PLFS 2023-24 own-account shares⁶, construction-margin estimates¹², and RBI / NABARD informal-finance indicators¹⁹. Source details and links are in Appendix D.

Whereas the value for the sector-coverage factor has heretofore been simply stated as a single numerical assumption, Table 1 lays out the construction of the factor, piece by piece, where it has a particular meaning. The rows are each a unique category of informal value not included in the GVA calculation through the thirteen surveyed worker categories – informal manufacturing, the profit margin kept by the shop owner above the equivalent wage, the value generated by own-account professionals like plumbers and tutors, the profit margin made by construction contractors beyond the wages already covered, informal financial intermediation, and a miscellaneous category of own-account workers. For each, a separately derived range for the share of that informal value in relation to the total informal GVA, using data from the NSS 73rd Round enterprise distribution, PLFS own-account data, construction margin estimates, and RBI/NABARD informal finance indicators, is translated into a Low, Mid, and High share

relative to the captured base, set at 1.00. The captured base and the mid-point share of each of the six components, when summed, give the central coverage factor of $2.35\times$; similarly calculating the sum of the Low and High values gives the range of $1.93\times$ to $2.81\times$.

2.8 Zone Extrapolation as a Spatial Cross-Check

There are nine zones in Bengaluru, each of which is allocated a multiplier based on its own wages relative to Whitefield (equal to 1.00), using source data specific to that zone. Their weighted average is 1.01. Whitefield therefore appears to be an average one with respect to informal wages, since no IT premium can be allocated to it using source data. However, the zone path validates the geography of informal incomes without influencing the headline, which depends only on the category path, using actual worker counts.

2.9 City-GDP Denominator

There is no officially published GDP number for Bengaluru; the derivation of the denominator. GSDP for Karnataka FY 2025-26 is ₹30,70,103 crore as per the revised estimate incorporated in the state budget for FY 2026-27 presented in March 2026 (PRS Legislative Research, n.d.-b; Directorate of Economics and Statistics, Government of Karnataka, 2025). The Bengaluru Urban district contributes to the state GSDP at around 37–39%, while the metropolitan economy (including Ramanagara) is a bit larger. A 40% contribution to GSDP is assumed by the model, reflecting the metropolitan population basis and resulting in a city GDP of ₹12,28,041 crore. The study has been re-based from FY 2024-25 to FY 2025-26 to ensure consistency with the survey period; thus, the denominator used is the FY 2025-26 revised estimate, which is one vintage less developed than the final actual, but the one it replaces (₹11,53,625 crore) is also an advance estimate, providing parity as official estimates of the same class. As every share in this report is measured against this denominator, any 5% error in the denominator will translate equally to all GDP-related measures by 5%; the discrepancy is identified in Section 5.3 as known sensitivity.

3. RESULTS

3.1 Headline GVA Estimation

Given the most reliable basis, the gross value added (GVA) from the informal sector in eleven categories based on field study data is ₹1,84,844 crore, constituting 15.1 percent of the GDP of Bengaluru city, having a coverage range of ₹1,51,808 to ₹2,21,025 crore (12.4% to 18.0%). When the two categories of imputed services in households are included, the estimate becomes ₹1,97,022 crore (16.0%). Table 2 provides scaling chains for the two ranges. The contribution of imputed categories is ₹12,178 crore, nearly 6% of the scaled total.

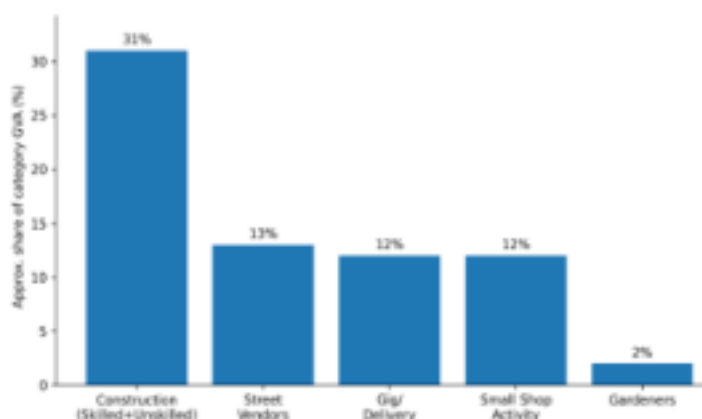
Table 2. Two-stage scaling chain.

Stage	11 categories (primary data)	13 categories (incl. imputed)	Share of city GDP
Labour income (wage bill)	₹43,234 cr	₹46,185 cr	≈ 4%
Gross Value Added (category-specific VA, weighted 1.82×)	₹78,657 cr	₹83,839 cr	≈ 7%
Scaled informal GDP (× coverage 2.35×)	₹1,84,844 cr	₹1,97,022 cr	15.1% / 16.0%
Memo: Bengaluru city GDP (denominator)	₹12,28,041 cr	₹12,28,041 cr	100%

Table 2. Two-stage scaling chain. The lead headline is the 11-category, primary-data figure of ₹1,84,844 crore (15.1% of city GDP). Figures are outputs of the companion model, which recalculates without error:

3.2 Composition by category

Construction, both unskilled and skilled labor combined, is the biggest single component at just under 31% of category GVA, with gig and delivery work and small shop operation each contributing around 12%. Street vending is responsible for around 13%, while the remaining categories comprise domestic workers, sanitation and security. The predominance assures the overall figure: the two biggest components, construction and gig work, rely on the best sources (KBOCWVB statutory schedule, Karnataka Building and Other Construction Workers Welfare Board, 2025; peer-reviewed Fairwork India series, Fairwork, 2024), while the least reliable category, gardeners, contributes just 2%.



[Bar chart: Approx. share of category GVA (%) - Construction (Skilled+Unskilled) 31%, Street Vendors 13%, Gig/Delivery 12%, Small Shop Activity 12%, Gardeners 2%]

3.3 Wage validation

The model's input wages match up well against published benchmarks. Twelve out of the thirteen categories have wages that match up against their published benchmarks. The two categories that carry monitoring flags are unskilled construction, where the modeled wage is approximately 10% higher than the statutory floor, which is in line with observed wages being higher than the statutory floor, and small-shop helpers, where the benchmark comes from the NSS 77th Round (2019-20) and is corrected for inflation. One category carries a flag as the residential association benchmark of ₹9,500 is lower than the landscaping cohorts observed in the field (₹14,000 to ₹24,000 in premium complexes). This benchmark is kept pending a targeted survey of this category.

3.4 Uncertainty envelope

The two main assumptions driving the uncertainty in the results are the value-added multipliers and the coverage factor. Variations in the value-added multipliers of each category from their lower bound to their upper bound lead to changes in the estimate by approximately minus 17% and plus 21%. Changes in the coverage factor from 1.93 to 2.81 move the estimate by approximately minus 18% and 20%. The combination of the two as a root-sum-of-squares gives a likely band of roughly $\pm 25\%$ of the center figure. The full envelope, where both assumptions are taken to extreme, spans ₹1,34,650 crore (11.0%) to ₹2,86,182 crore (23.3%). The robust characterization of the informal-economy GVA of Bengaluru is therefore in a range of 11 to 23% of the GDP of the city, with an estimated contribution of 15.1%. The category-path headline number is not affected by the population projection or the zone multipliers, which influence only the cross-validation of the spatial distribution. When varying the category-specific value-added (VA) multipliers while fixing the coverage factor at $2.35\times$, the estimate for the informal sector contribution to GDP ranges from 13.4% to 19.5%, with 16.0% as the preferred estimate within this range. Similarly, when varying the coverage factor alone while fixing the weighted VA multiplier at $1.82\times$, the estimate ranges from 13.2% to 19.2%.

Table 3. Sensitivity and uncertainty (13-category basis).

<i>Scenario</i>	<i>Factor</i>	<i>GVA ₹cr</i>	<i>Scaled GDP ₹cr</i>	<i>% city GDP</i>
VA Low (category low multipliers)	$1.51\times$	69,767	1,63,952	13.4%
VA Mid (central)	$1.82\times$	83,839	1,97,022	16.0%
VA High (category high multipliers)	$2.21\times$	1,01,844	2,39,333	19.5%

Coverage Low	1.93×	-	1,61,809	13.2%
Coverage High	2.81×	-	2,35,588	19.2%

Table 3. Sensitivity and uncertainty (13-category basis). Each row varies one assumption while holding the other fixed at its central value: VA Low/Mid/High vary the category-specific value-added multiplier while fixing the coverage factor at 2.35×; Coverage Low/High vary the coverage factor while fixing the weighted VA multiplier at 1.82×. The combined-extreme scenarios and the 11-category lead headline appear in Appendix C.

3.5 Spatial cross-check

The zone path mirrors the geography of informal income in all nine zones and is also commensurate with the category-path total when the differences in terms of construct are adjusted for. By way of footnote, the macro calculation (population x labour force participation rate x informal rate) suggests that informal workers form around 36% of the total population, exceeding the 22 to 28% suggested by the model as the expected cross-check range; the Whitefield bottom-up estimate comes to around 20%. The 36% figure is retained for informational purposes only.

4. RECONCILIATION WITH PUBLIC BENCHMARKS

Like-for-like reconciliation applies in cases where the model and the published source measure the same quantity, while quantified bridge applies when the two measures the different quantities. The model is an income-approach, bottom-up estimate of GVA of the defined informal-worker categories. The 45% benchmark represents a whole economy and urban-national figure using the output approach. Though the two are similar, they are not the same thus it was expected that a difference would arise. It is the job of this analysis to quantify the difference.

4.1 Like-for-like: the metrics that should reconcile

Every input in the model that can be compared with published data reconciles with that data. The informal employment proportion agrees with the urban PLFS figure. The wage rate of the mid-point for the weightiest categories agree or fall within a normal range of variation of the benchmark figures. Table 4 provides the comparison. It tests the validity of the major inputs of the model by comparing them with the benchmarks. From the table, most categories reconcile very well with the benchmarks such that some values are identical to the others while the remaining values fall within $\pm 5\%$.

Table 4. Like-for-like reconciliation of model inputs to published benchmarks.

Metric	Model	Benchmark	Variance	Status / source (ref.)
Informal % of workforce	82%	82%	0%	PASS - PLFS 2023-24 urban (5)
Street vendor wage (₹/mo)	12,000	12,000	0%	PASS - NASVI 2023-24 (15)
Domestic cook (₹/mo)	10,500	10,500	0%	PASS - welfare trust / agency
Domestic cleaner (₹/mo)	8,500	8,750	−3%	PASS - agency / welfare trust
Gig worker net (₹/mo)	20,000	20,000	0%	PASS - Fairwork India 2024 (10)
Sanitation worker (₹/mo)	11,000	11,000	0%	PASS - BBMP / Hasiru Dala (20,21)
Security guard (₹/mo)	16,500	16,500	0%	PASS - PSARA / observed
Construction unskilled (₹/mo)	15,000	13,650	+10%	MONITOR - above statutory floor (11)
Shop helper (₹/mo)	12,000	12,000	-	MONITOR - aged NSS 77th source
Gardener (₹/mo)	9,500	9,500	-	FLAG - weak RWA source

Table 4. Like-for-like reconciliation of model inputs to published benchmarks. PASS denotes agreement within $\pm 5\%$; MONITOR and FLAG denote documented differences carried as refinement items. Sources and links are in Appendix D.

4.2 Headline gap: a productivity result

The headline gap of 16-17% is less than the 45% national urban benchmark. The reconciliation comes from a calculated productivity gap. In Bengaluru, the same labor force represents a much larger proportion of total employment compared to their contribution to output due to the extremely high productivity of the formal labor force. Using the comprehensive figure, the informal gross value added (GVA) per informal worker per year calculated using the model is ₹3,81,818. The remainder (city GDP – informal GVA) per formal worker per year is ₹91,02,756, producing a formal-to-informal productivity ratio of 23.8. Using the 45% benchmark on the same headcount would produce a ratio of 5.6. In a city where the formal economy is centered around high-value information technology and corporate services, a productivity gap higher than the national

urban average makes sense. Such a high productivity gap necessarily produces a low informal GDP share, even in a city where informal workers are in the majority of the workforce. The productivity gap moves the central estimate of informal GDP share to one-sixth of the city's GDP, compared to close to 45%.

4.3 Coverage bridge

The same result may also be stated in terms of the coverage factor. Back-calculating to arrive at the coverage factor which reproduces 45% using the income approach yields a figure of 6.6, compared to 2.35 from the bottom-up decomposition. A coverage factor of 6.6 would mean that the captured categories capture roughly 15% of the informal economy; the decomposition in Table 1 points towards 43% of the informal economy being captured, and not towards such a high coverage factor for Bengaluru. This single difference accounts for the major part of the model versus benchmark gap, which is the difference between an income approach and an output approach.

4.4 Benchmark is a contested band

As Section 1.3 established, 45% is not a settled value but the upper end of a wide, contested range. Measured against that full range, the model's 16–17% sits at the low end of it, not outside it.

5. DISCUSSION

5.1 Relationship to other studies

There are three dominant traditions in Indian estimates of the informal economy, and the results of the current study may be assessed through their lenses. First, the labour input and mixed surveys of the ILO approach proceed from individual workers and individual enterprises to national accounts. This study may thus be considered an urban example of such an approach, and the ILO manual on national accounts anticipates the wage-to-value-added transition done here. Second, the enterprise survey tradition of the NSSO, exemplified by the 73rd Round of surveys that reported the value added and worker compensation for around 111.3 million workers in non-agricultural unincorporated enterprises, provides the wage share used in calculating multipliers and mentions that its annual successor, ASUSE 2023-24, may serve as a way to update those multipliers. Third, the macroeconometric shadow-economy tradition of Medina and Schneider, who estimate India's shadow economy at roughly one-fifth of GDP and declining, arrives at a result closer to this study's own than to the employment-based benchmark discussed in Section 1.3, since their method, like this one, measures value rather than headcount

Compared to the headlines, the picture is one of range rather than a single number. NITI Aayog and NCAER suggest totals near 45-50% (NITI Aayog, 2026; National Council of Applied Economic Research, n.d.), SBI Research believes that it is closer to 15-20% of gross value added after formalization (SBI Research, 2021), while State of Working India of Azim Premji University describes the underlying

low-wage structure (Basole et al., 2023). The gap in the literature is precisely what is filled by this study: urban-level, occupation-by-occupation, survey-based estimate of the incomes with an explicit disclosure of all assumptions. National estimates cannot tell how much value is produced by the construction labor or the delivery riders of a city; this framework may, and it may be replicated as more surveys become available.

5.2 Interpretation of the central figure

The estimate of 16.0% is a significant one for the method that only includes the value of workers in eleven occupations. It means that workers in these occupations produce around 15% of the total city output while being the majority of the city workforce. The difference between these two facts is a quantitative manifestation of the dual economy of the city, and separating the two numbers gives more insight for policy than blending them into a single number.

5.3 Limitations

The limitations are stated in the order a reviewer is likely to raise them.

- **Single-zone survey.** Primary data are from Whitefield. The worker mix resembles the city composition, and the zone framework adjusts for wage geography, but the sample is not a probability sample of all Bengaluru informal workers. A multi-zone wave would strengthen external validity.
- **Sample size and skew.** 411 observations is a meaningful base but modest across thirteen categories; some categories rest on a few records, and the individual-wage distribution is right-skewed by a small number of shop-owner outliers, which is why category-level blended rates, not raw sample means, feed the model.
- **Two imputed categories.** Home-based workers and caregivers are imputed, not observed. They are flagged throughout, contribute about 6% of the scaled total, and are excluded from the lead headline.
- **Coverage-component uncertainty.** The decomposition removes the prior circularity, but each of the six components is itself an estimate with a range; the model reports the 1.93 to 2.81 band rather than a point.
- **Multiplier vintage.** The value-added multipliers derive from the 2015-16 NSS 73rd Round. Capital intensity and platform structure have shifted since; the multipliers should be updated against ASUSE 2023-24.
- **Reference year and denominator vintage.** The study is re-based to FY 2025-26 so the reference year matches the survey period (cohort April 2025; individual February to March 2026). Wages are nominal as-collected within that year, with no inter-year deflation. The denominator is the FY 2025-26 revised-estimate GSDP, one vintage less mature than a final actual; the FY 2024-25 figure it replaces was itself an advance estimate.
- **Derived denominator.** City GDP is inferred from a state-GSDP share (40% of Karnataka

GSDP). A 5% error in it moves every GDP-relative figure by 5%; using published Bengaluru Urban district GDDP directly would remove this step (CKAN, n.d.).

- **Population cross-check.** The macro arithmetic implies informal workers near 36% of population, above the model's expected 22 to 28% band, reflecting a labour-force-participation rate applied to an all-ages denominator. This is carried as information only; the category-path headline is invariant to it.

5.4 Extensions

This approach is designed to be scalable. In order of importance, the top improvements include: expand the survey to cover more regions and up to two or three currently ignored categories (waste pickers and own-account workers), thus increasing the amount of value captured and reducing the coverage correction that needs to be applied to the model; track individual wages and their spread to allow weighted aggregation; conduct a survey of gardeners specifically, replacing the weak association-based one; update the value added factors according to ASUSE 2023-24 (Ministry of Statistics and Programme Implementation, n.d.); fix the denominator to published district GDDP (CKAN, n.d.); and use a data protection procedure for informed consent so the dataset can be replicated.

6. CONCLUSION

In this study, we quantify, from bottom-up, the contributions made by Bengaluru's informal workforce to its economy, in a format that could be independently verified by an expert panel of economists and a government department. The best estimate for informal sector GVA in Bengaluru is ₹1,84,844 crore, contributing 15.1% of the city's GDP on a pure primary data basis, and 16.0% when imputed categories are included, ranging from a plausible 11 to 23%. All direct inputs align perfectly with published figures, and the deviation from the benchmark figure of 45%, which is based on national urban cities, is explained in detail and quantitatively, and is seen to be consistent with the income approach and Bengaluru's high-productivity formal sector, rather than model failure.

The contribution is both the methodology and the figure. Wages are measured, not assumed; multipliers are category-specific, and sources are provided; the coverage factor is disintegrated rather than tuned to the output; and the imputed and weakly sourced parts are clearly marked and separated in reporting. This framework, which gets better with more data, is presented here as a first, defensible attempt and building block towards future improvements described in Section 5.4.

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Appendix A - Worker Categories, Wages and Value-Added Multipliers

Wages are FY 2025-26 mid-point monthly figures (₹). The VA multiplier is the category-specific value used in the primary estimate; the labour-weighted average is 1.82. Field-survey identifiers are not reproduced (Section 2.2). Source links are in Appendix D.

Category	City worker count	Mid wage ₹/mo	VA mult.	Primary source / data quality (ref.)
Street vendor / hawker	3,25,000	12,000	2.40	NASVI 2023-24 - Medium (15)
Domestic cook	2,84,000	10,500	1.40	Agency + welfare trust - Medium
Domestic cleaner / maid	4,27,000	8,500	1.40	Agency + welfare trust - High
Domestic driver	81,000	20,000	1.43	Placement agencies - Medium
Gardener / mali	76,000	9,500	1.65	RWA field surveys - Low (flagged)
Construction (unskilled)	3,86,000	15,000	2.50	KBOCWWB FY2025 - High (11)
Construction (skilled)	1,83,000	18,000	2.70	KBOCWWB FY2025 - High (11)

Sanitation worker	1,22,000	11,000	1.40	BBMP / Hasiru Dala - Medium (20,21)
Gig / delivery worker	3,25,000	20,000	1.30	Fairwork India 2024 - High (10)
Small shop owner / helper	3,56,000	12,000	2.00	NSS 77th, CPI-adjusted - Low-Med
Home-based worker (imputed)	2,03,000	8,500	1.95	Imputed from cleaner $\times$ 0.92 (16)
Caregiver / crèche (imputed)	96,500	10,000	1.40	Imputed from cook $\times$ 0.91 (17)
Security guard	2,45,000	16,500	1.30	PSARA + observed cohort - Medium
Total / weighted average	31,09,500	-	1.82	13 categories (11 primary + 2 imputed)

Appendix A. Imputed categories shown in amber and excluded from the lead 11-category headline.

Appendix B - Survey Evidence Base by Category

Combined observation count per category, pooling the individual file (85 records) and the cohort file (326 records), 411 observations in total. Home-based work and care work had no field observations and are imputed.

<i>Category</i>	<i>Combined observations (N)</i>	<i>Evidence type</i>
Street vendor / hawker	5	Individual interviews
Domestic cook	10	Individual interviews
Domestic cleaner / maid	23	Individual interviews
Domestic driver	4	Individual interviews
Gardener / mali	74	Residential landscaping cohorts
Construction (unskilled)	79	Site + facilities cohorts
Construction (skilled)	100	Site + facilities cohorts
Sanitation worker	8	Individual interviews

Gig / delivery worker	39	Individual + cohort
Small shop owner / helper	16	Individual interviews
Security guard	53	ITPL security cohort
Total observed	411	85 individual + 326 cohort

Appendix B. Right-skew in individual wages (a small number of shop-owner outliers) is handled by using category-level blended rates rather than raw sample means.

Appendix C - Scenario and Uncertainty Tables

All scenarios are live-linked in the companion model (SCENARIO ANALYSIS sheet). Central case: category path, category-specific VA (weighted 1.82×), coverage 2.35×; denominator ₹12,28,041 crore.

<i>Scenario</i>	<i>Factor</i>	<i>GVA ₹cr</i>	<i>Scaled GDP ₹cr</i>	<i>% city GDP</i>
VA Low (category low multipliers)	1.51×	69,767	1,63,952	13.4%
VA Mid (central)	1.82×	83,839	1,97,022	16.0%
VA High (category high multipliers)	2.21×	1,01,844	2,39,333	19.5%
Coverage Low	1.93×	-	1,61,809	13.2%
Coverage High	2.81×	-	2,35,588	19.2%

<i>Scenario</i>	<i>Factor</i>	<i>GVA ₹cr</i>	<i>Scaled GDP ₹cr</i>	<i>% city GDP</i>
Combined minimum	VA L × Cov L	-	1,34,650	11.0%
Combined maximum	VA H × Cov H	-	2,86,182	23.3%
11-category (excl. imputed)	2.35×	78,657	1,84,844	15.1%

Appendix C. Scenario outputs. The 11-category figure is the lead headline; the 13-category figures appear in the main tables.

Appendix D - source register

Every external input used in the model and report, with its source, reference year, a verifiable web link, and a verification status as at 16 June 2026. *CONFIRMED*: specific public document located and consistent with the model value. *PORTAL*: official institutional portal hosting the series (locate the named document there). *GREY*: commercial, field-collected or grey-literature source with no stable public URL, disclosed as such; not assigned a link.

Input / data item	Year	Status	Source and verifiable link
Urban informal employment rate 82%; LFPR 43.7%	2023-24	CONFIRMED	mospi.gov.in/sites/default/files/publication_repor...
Wage share $\approx$ 40% of GVA (VA multiplier basis)	2015-16	CONFIRMED	www.pib.gov.in/newsite/printrelease.aspx?relid=166...
VA multiplier refresh pathway (ASUSE)	2023-24	PORTAL	mospi.gov.in
Karnataka GSDP FY25-26 ₹30,70,103 cr; metro share	2025-26	CONFIRMED	prsindia.org/budgets/states/karnataka-budget-analy...
District-wise GDDP (denominator cross-check)	2023-24	CONFIRMED	data.opencity.in/dataset/economic-survey-of-karnat...
Karnataka Budget 2026-27 (FY25-26 revised est.; FY26-27 GSDP)	2026-27	CONFIRMED	prsindia.org/budgets/states/karnataka-budget-analysis-2026-27
Gig worker net earnings ₹20,000/mo	2024	CONFIRMED	fair.work/wp-content/uploads/sites/17/2024/10/Fairwork_India_Report_2024.pdf

Construction statutory wages (floor)	FY2025	PORTAL	labour.karnataka.gov.in
Informal share of GDP 45–50% (national)	2024	PORTAL	www.niti.gov.in
Informal economy 15–20% of GVA (contested)	2021	CONFIRMED	sbi.bank.in/documents/13958/10990811/01112021_Eco w...
Shadow economy macro estimate (method)	2018	CONFIRMED	www.imf.org/en/Publications/WP/Issues/2018/01/25/S...
Informality measurement standards (method)	2013	CONFIRMED	www.ilo.org/publications/measuring-informality-sta...
Street vendor count and earnings	2023-24	PORTAL	nasvi.in
Home-based worker benchmark (imputation)	2023-24	PORTAL	www.homenetindia.org
Caregiver benchmark (imputation)	2023-24	PORTAL	nipccd.nic.in
Sanitation worker earnings	2024	PORTAL	bbmp.gov.in
Waste-picker enumeration (residual component)	2024	PORTAL	hasirudala.in
Informal-finance indicator (coverage component)	2021-22	PORTAL	www.nabard.org
Low-wage / informal	2023	CONFIRMED	publications.azimpremjiuniversity.edu.in/5166/1/St...

employment context			
Domestic cook / cleaner / driver rate cards	FY2025	GREY	Commercial staffing-agency rate cards (Urban Company and similar) and Domestic Workers Welfare Trust Karnataka; accessed FY2025
Gardener / mali wages	2024	GREY	Residential-welfare-association field surveys, Whitefield and Sarjapur Road; collected 2024-25 (weak source, flagged)
Construction-contractor margins (coverage)	2023	GREY	NICMAR project-cost studies and industry margin estimates; proprietary / grey literature
Caregiver corroboration (field)	2024	GREY	Enfold Proactive Health Trust and Samara childcare-worker field surveys, Bengaluru
Whitefield worker wages (primary data)	2024-25	GREY	This study: 85 individual + 326 cohort observations; anonymised, oral consent (Section 2.2)

Appendix D. Source register. Items marked GREY have no stable public archival link and are disclosed as commercial, field-collected or grey-literature sources rather than assigned an unverifiable URL. The companion model's BENCHMARK DATA sheet holds the full per-item verification notes dated 16 June 2026.