The Economics of Geographical Indications:

Evidence from the Indian Tea Industry

A Thesis Submitted

To

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In Partial Fulfilment of the Requirement for the

Degree of Doctor of Philosophy

By

Bivek Tamang

Department of Economics

School of Social Sciences

Under the Supervision of

Dr. Rajesh Raj S.N.

Department of Economics

Sikkim University

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...सामदुर, तादोंग -737102
...सिक्किम, भारत
...592-251212, 251415, 251656
... -251067
... - www.cus.ac.in

सिक्किम विश्वविद्यालय
SIKKIM UNIVERSITY
(भारत के संसद के अधिनियम द्वारा वर्ष 2007 में स्थापित और नैक (एनएएसी) द्वारा वर्ष 2015 में प्रत्यायित केंद्रीय विश्वविद्यालय)
(A central university established by an Act of Parliament of India in 2007 and accredited by NAAC in 2015)

6th Mile, Samdur,Tadong -737102
Gangtok, Sikkim, India
Ph. 03592-251212, 251415, 251656
Telefax: 251067
Website: www.cus.ac.in

Date: 26/06/2024

DECLARATION

I, Bivek Tamang, hereby declare that the research work embodied in the thesis entitled **"The Economics of Geographical Indications: Evidence from the Indian Tea Industry"** submitted to Sikkim University for the award of the degree of Doctor of Philosophy, in my original work and that to the best of my knowledge it contains no materials previously published or written by others. Whenever contributions of others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgement of collaborative research and discussions.

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26.06.24

Bivek Tamang
PhD Scholar
Roll No.: 16PDEC02
Reg. No.: 16SU19579
Department of Economics,
Sikkim University, Sikkim

We recommend this thesis be placed before the examiners for the evaluation.

26.06.24

Dr, Rajesh Raj S. N.
Supervisor
Associate Professor
Department of Economics
School of Social Sciences

Dr. Manesh Choubey
Head of the Department
Associate Professor
Department of Economics
School of Social Sciences

अध्यक्ष
Head
अर्थशास्त्र विभाग
Department of Economics
सिक्किम विश्वविद्यालय
Sikkim University

सामदुर, तादोंग -737102
सिक्किम, भारत
2-251212, 251415, 251656
-251067
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(A central university established by an Act of Parliament of India in 2007 and accredited by NAAC in 2015)

Date: 26/06/2024

CERTIFICATE

This is to certify that the thesis entitled **"The Economics of Geographical Indications: Evidence from the Indian Tea Industry"** submitted to Sikkim University for partial fulfillment of the degree of **Doctor of Philosophy in Economics,** embodies the result of bonafide research work carried out by **Bivek Tamang,** Roll No. 16PDEC02, Registration No. 16SU19579, under my guidance and direct supervision. The contents of the thesis in full or in parts have not been submitted to any other institute or University for the award of any degree or diploma.

All the assistance and help received during the research work have been duly acknowledged by him.

I recommend this thesis to be placed before the examiners for evaluation.

26.06.24

Dr. Rajesh Raj S. N.
Supervisor
Associate Professor and Head
Department of Economics
School of Social Sciences

…ल, सामदुर, तादोंग -737102
…, सिक्किम, भारत
…03592-251212, 251415, 251656
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Ph. 03592-251212, 251415, 251656
Telefax: 251067
Website: www.cus.ac.in

Date: 26/06/2024

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"The Economics of Geographical Indications: Evidence from the Indian Tea Industry"

Submitted by **Bivek Tamang** under the supervision of **Dr. Rajesh Raj S.N.**, Associate Professor in the Department of Economics, School of Social Sciences, Sikkim University, Gangtok.

26.06.24

(Bivek Tamang)
Signature of Research Scholar

26.06.24

(Dr. Rajesh Raj S. N.)
Signature of Supervisor

Vetted by Librarian

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Ph.D. teaches you to keep going even when it seems impossible at times. Guess this is what we call resilience. God knows how challenging the PhD journey has been for me. And I thank God and my Supervisor for the completion now.

Alas, PhD in economics is not for the faint-hearted!!!

- **Bivek Tamang**

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LIST OF ABBREVIATIONS

ASI	Annual Survey of Industries
ATT	Average Treatment Effect
BH	Base Heterogeneity
CAGR	Compound Annual Growth rate
CPI	Consumer Price Index
CSO	Central Statistical Office
ESR	Exogenous Switching Regression
ETR	Endogenous Treatment Regression
EU	European Union
EUIPO	European Union Intellectual Property Office
F&B	Food and Beverage
FDI	Foreign Direct Investment
GIs	Geographical Indications
IPRs	Intellectual Property Rights
IVTR	Instrumental Variable Treatment Regression
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Scheme
NGI	Non-Geographical Indication
NIC	National Industrial Classifications
OLS	Ordinary Least Squares
PDO	Protected Designations of Origin
PSM-DID	Propensity Score Matching - Difference-in-Difference
R&D	Research and Development
RBI	Reserve Bank of India
RIF	Recentered Influence Functions
RLOs	Regional Labour Offices
SC	Scheduled Caste
SGRY	Swarnajayanti Gram Swarozgar Yojana
ST	Scheduled Tribe
TBI	Tea Board of India

TFP	Total Factor Productivity
TH	Transactional Heterogeneity
TRIPS	Trade-Related Aspects of Intellectual Property Rights
TTU	Average Treatment Effect on the Untreated
UQR	Unconditional Quantile Regression
WPI	Wholesale Price Index
WTO	World Trade Organization

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Intellectual Property Rights (IPRs) grant exclusive rights and incentives to creators, promoting innovation across various fields. Research emphasizes that robust IPR protection attracts more investments, thereby positively impacting innovation and economic growth (Neves et al., 2021). For instance, a study by the European Union Intellectual Property Office (EUIPO) shows that European Union (EU) firms with IPRs experienced 20% higher revenues per employee, paid 19% higher wages, and contributed to 29% of employment, and 45% of GDP within the EU compared to their counterparts without IPRs (EUIPO, 2021). Studies highlight an indirect link between IPRs and growth by stimulating investments in factors like research and development (R&D) and physical capital (Park and Ginarte, 2007). The global IPR framework witnessed a significant transformation with the establishment of the Trade-Related Aspects of Intellectual Property Rights (TRIPS) Agreement. TRIPS[1] is a multilateral agreement on intellectual property under the WTO and is composed of seven elements: Copyrights, Trademarks, Geographical Indications, Industrial Designs, Patents, Integrated Circuits Layout Designs, and Undisclosed Information and Trade Secrets. TRIPS sets the minimum standard for IPR protection, which the member countries of the WTO must uphold, representing a milestone in the history of international intellectual property agreements (Maskus, 2000; Dixon and Greenhalgh, 2002).

[1] https://www.wto.org/english/tratop_e/trips_e/intel2_e.htm

Various intellectual property rights (IPRs) exist, and among them, trademarks are widely utilized. Exemplified by the iconic NIKE "swoosh,"[2] trademarks play a pivotal role in differentiating products or services. Despite not conveying detailed product information, trademarks promote consumer recognition and expectations. This limitation prompted the development of Geographical Indications (GIs) laws, protecting regional identities like Darjeeling tea or Champagne. GIs offer legal protection, ensuring informed consumer choices and preventing misuse through *sui generis* laws. Ultimately, GIs serve as both anti-counterfeiting tools and indicators of quality, thereby influencing consumer purchasing decisions.

The primary function of GIs is to inform consumers about the true geographic origin of the goods, emphasizing unique qualities attributed to both geographical and local human factors, making replications impractical (Addor and Grazioli, 2002). These distinct characteristics permit producers to differentiate their products and offer unmatched quality, thereby leading to potential premium prices and economic benefits for producers, farmers, rural communities, and entrepreneurs (Bramley et. al., 2007). This reward encourages innovation and the improvement of traditional production methods to maintain high quality (Downes and Laird, 1999; Das, 2006). GIs also serve a consumer policy objective by presenting clear and credible information to consumers (Réquillart, 2007). The geographical association and consumer recognition of GIs provide ‘decisive commercial and trade advantages’ to producers (Pike, 2015). However, the significant economic gains from GI products make them susceptible to misuse, known as “passing-off”[3], by unethical businessmen and companies engaging

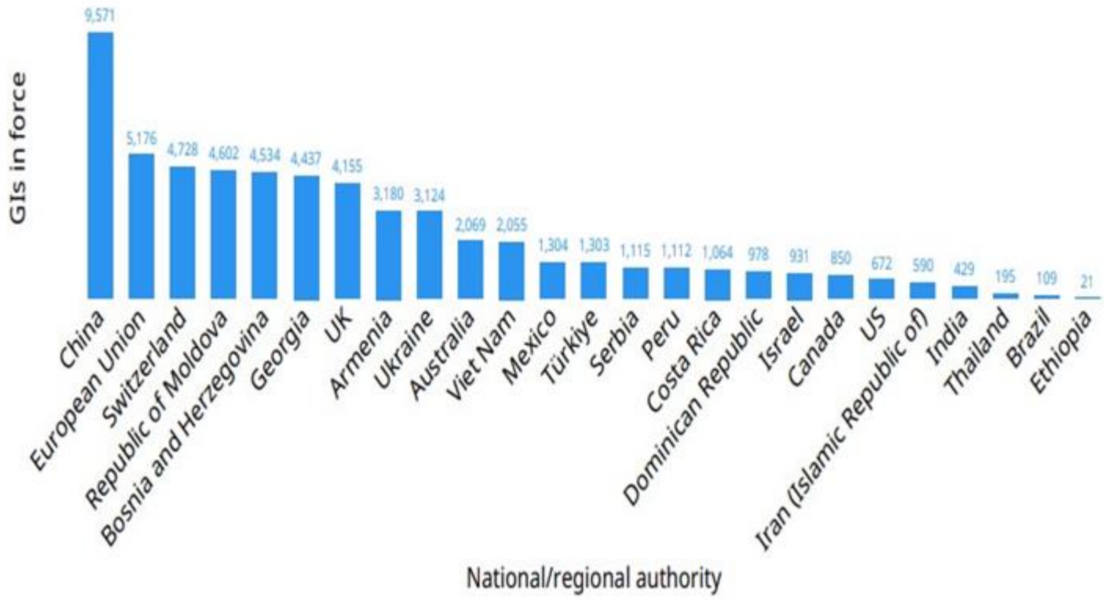
[2] The NIKE "swoosh" is a registered trademark of Nike, Inc., and serves as a distinctive logo for their brand.
[3] Passing-off refers to the unauthorised use of someone’s brand to trade goods.

in free-riding[4] practices. Such unethical practices pose a serious risk of damaging the goodwill, reputation, and economic rewards of the genuine manufacturer/owner (Das, 2006; Burberry, 2009; Moor, 2007).

GIs have gained prominence across the globe, with China and European countries leading in their widespread adoption (Figure 1). Despite their increasing use worldwide, there have been limited attempts to gauge the economic effects of GI protection. Existing studies have largely approached GIs from a legal standpoint. Much research remains to be done on the underlying economic impact of geographical indications, leaving a significant gap in comprehending their economic implications, especially in a developing country context (Bramley et al., 2007). It is crucial to probe the economic benefits of GIs for producers and stakeholders, and this study aims to fill this void, particularly in the context of India. While anecdotal evidence suggests significant benefits for producers (Nanda et al., 2013), there is a scarcity of comprehensive evidence on the socio-economic impacts of GIs in India. This study addresses this gap, by focusing on India's surge in GI registrations over time since their implementation in 2003, providing an ideal setting for investigation (Figures 1.1 and 1.2). This rise in registrations is evident across states and sectors (Figures 1.2 and 1.3).

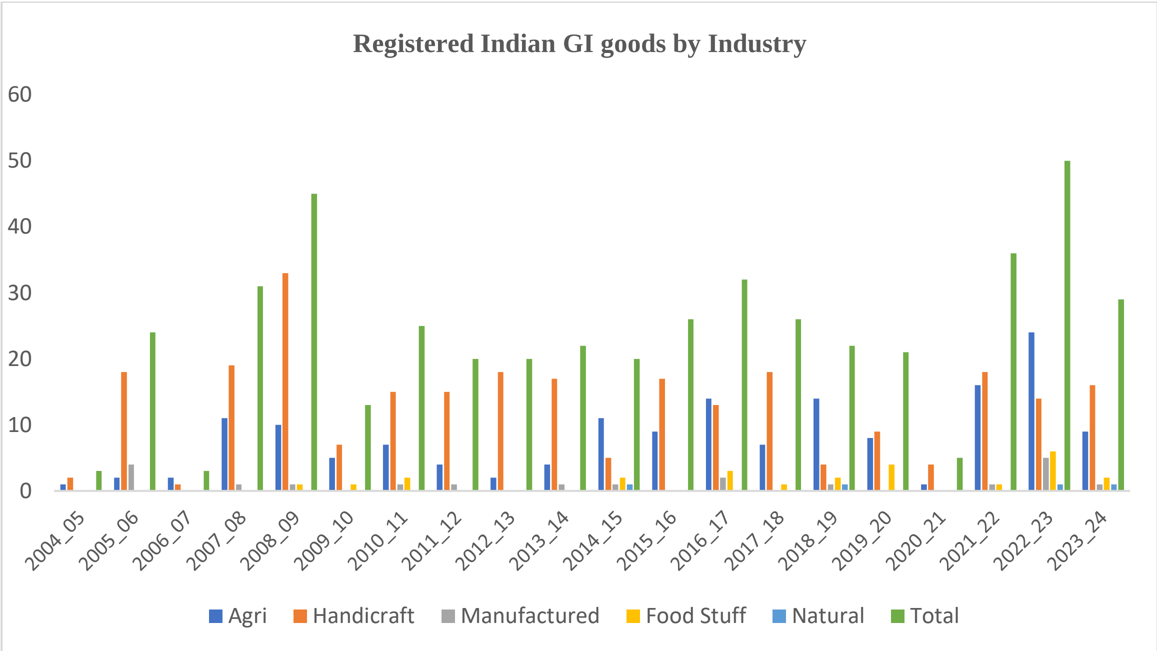
[4] Free-riding refers to the unscrupulous use of someone's reputation and goodwill to reap economic benefits from such usage.

Figure 1.1: Number of registered GIs (2022)



Source: WIPO, 2023.

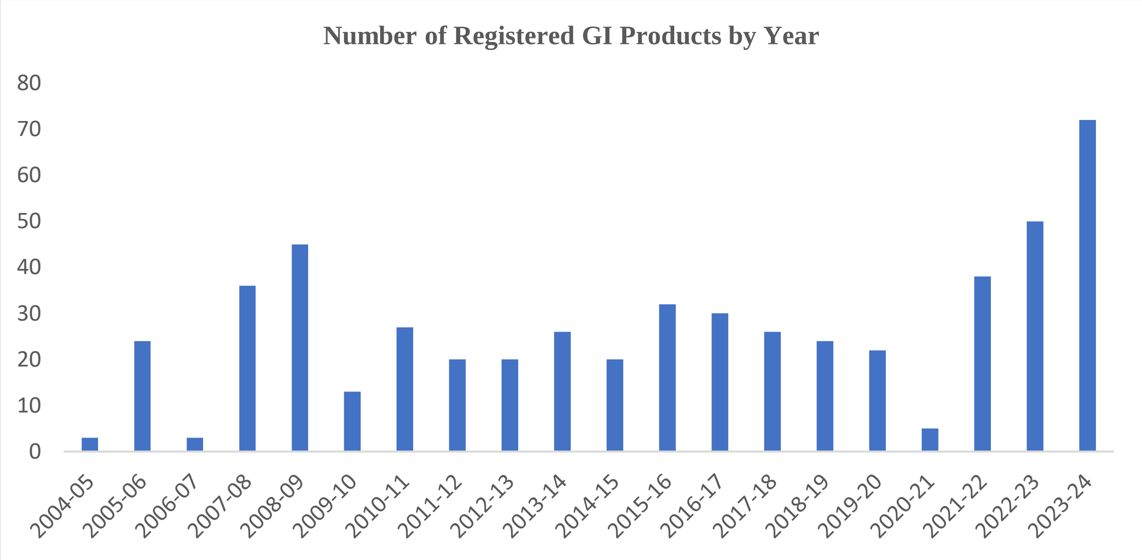
Figure 1.2: Trends of GI registration in India (2004-05 to 2023-2024)

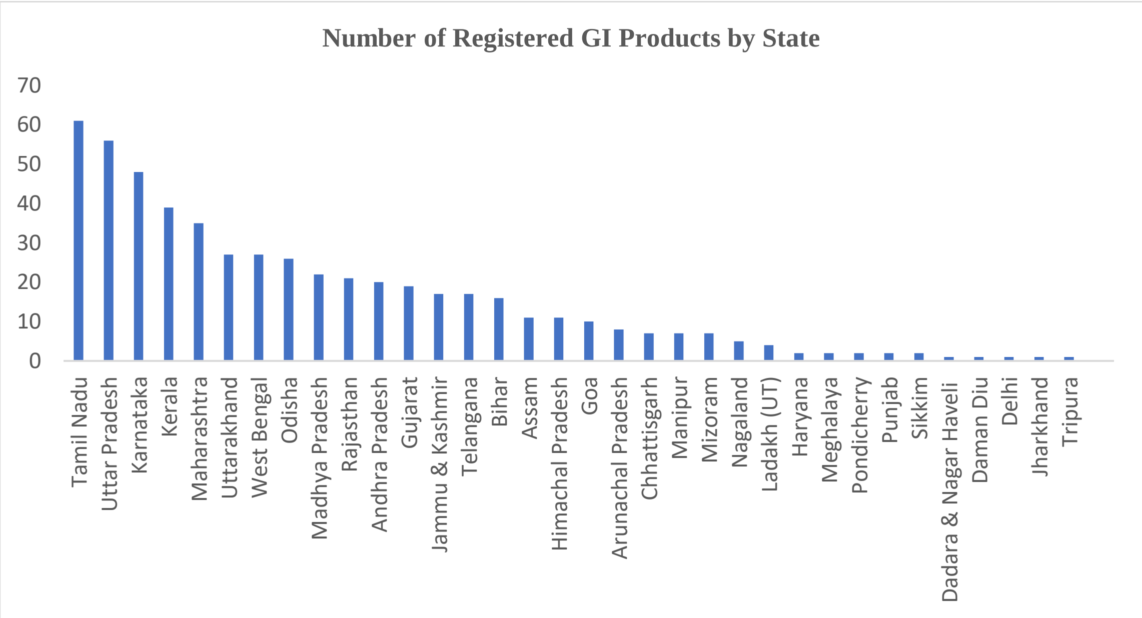


Source: Office of Controller General of Patents, Designs & Trade Marks, Department for Promotion of Industry and Internal Trade, Ministry of Commerce & Industry, Govt. of India. https://ipindia.gov.in/registered-gls.htm

Figure 1.3: Registered GI Products in India by Year and State

(2004-05 - 2023-24)





Source: Office of Controller General of Patents, Designs & Trade Marks, Department for Promotion of Industry and Internal Trade, Ministry of Commerce & Industry, Govt. of India. https://ipindia.gov.in/registered-gls.htm

This study focuses specifically on examining the effect of GI policy on the Indian tea industry, utilising the unique opportunity presented by the enactment of the GI Act in 1999 and Rules in 2003. The diverse evidence on GIs in the literature (Bowen and Zapata, 2009; Agostino and Trivieri, 2014; De Filippis et al., 2022) prompts an investigation into their effects at multiple levels – firm, garden, and worker. A positive effect is crucial for the industry's future growth and for improving rural employment and the rural economy. Recognised as a tool for industrial performance and territorial development, GIs have been proven crucial in European nations (Vital, 1999; Ploeg et. al., 2000; Bramley et al., 2009; Pike, 2015; Cei. et al., 2018). Given the economic effects of GI registration in the EU, it is essential for the Indian tea industry to achieve similar gains. However, the lack of empirical evidence using sound econometric tools on the GI effect in various countries, particularly in Asia, underscores the significance of this study. We have employed Annual Survey of Industries (ASI) data for whichever year the district identifier is available to substantiate the anecdotal evidence. Utilizing Annual Survey of Industries (ASI) data and complementing it with garden-level and primary surveys, we strive to substantiate and enrich our understanding of the role of GIs, addressing the current gap in secondary data sets.

1.2 Theoretical Perspectives and Empirical Literature

This section delves into the theories and impacts of IPRs in general and GIs in particular. It consists of two primary subsections. The first subsection (1.2.1) explores the economics of IPRs (including GIs) based on the theory of reputation and information. The second subsection (1.2.2) mainly reviews the empirical economic impacts and potential social costs of IPR protection. We also highlight the disparity in the distribution of IPR registration across nations.

1.2.1 Theoretical Perspectives

The relationship between intellectual property rights and reputation is multi-faceted, studied across disciplines including economics, sociology, psychology, marketing, and law. IPRs provide exclusive rights to the creators, enabling them to derive economic benefits from their creative efforts and reputation (Saha and Bhattacharya, 2011). A firm's reputation not only signifies output quality but also its ability to consistently deliver quality in the future (Vlašić and Langer, 2012). Similarly, GIs are essential for building reputations for consistently producing high-quality goods over extended periods (Gangjee, 2017). Consumer perception of trust, credibility, and authentic quality heavily influences the reputation of a producer, particularly for products where quality is not readily observable before consumption (Zago, 2015).

Misuse of a brand name or reputation can incur substantial costs, especially for established brands. The model of reputation building introduced by Shapiro demonstrates how competitors may exploit brand names to attract consumers willing to pay a premium for perceived quality (Grossman and Shapiro, 1986). GI registration aims to protect the IPRs of genuine traditional producers, granting them exclusive market rights to capitalize on quality reputation links for commercial advantage. Thus, GIs transform into reputational assets linking product quality with specific geographic origin, allowing producers to differentiate products, access niche markets, and potentially earn monopoly rents (Rangnekar, 2003; Yeung et al., 2008; Menapace and Moschini, 2012). As argued by Rangnekar (2004), the economics of GIs is fundamentally based on the economics of information and reputation.

The intersection of *Information Theory* and Geographical Indications (GIs) highlight their role in market signalling, consumer behaviour, and economic outcomes. GIs serve as powerful mechanisms to communicate origin, quality, and authenticity, addressing information asymmetry[5] between producers and consumers (Zago and Pick, 2004; Larson, 2007). However, issues such as adverse selection, where inferior products dominate due to quality uncertainty, highlight the importance of reliable information in markets (Akerlof, 1970; Stiglitz, 1981, 1989). GI protection aims to ensure that consumers receive accurate information, thereby mitigating risks associated with counterfeit goods and maintaining market integrity (Grossman and Shapiro, 1986).

GI registration often leads to collective monopolies, aimed at securing monopoly rents through entry barriers and controlling supply (Olsen, 1962). While this can potentially benefit right holders, it may also result in higher prices and restricted consumer choice, undermining allocative efficiency and consumer welfare. Importantly, the economic benefits derived from GI protection do not always trickle down to rural farmers or indigenous communities, who are often the primary producers of high-quality goods **(**Bramley et al., 2007). The enactment of GI laws was originally aimed at enhancing compensation and welfare in rural economies for these disadvantaged groups (Folkeson, 2005; Williams and Penker, 2009).

1.2.2 Empirical Literature

Intellectual property rights (IPRs) have gained significant importance for firms in the contemporary knowledge-driven economy, as indicated by the notable increase in their adoption (Zhang and Shan, 2023). IPRs are legal rights that protect the creations of the human mind, offering creators exclusive rights to incentivize their inventions, literary and artistic works, symbols, images, and business processes (WIPO, 2020).

[5] Is a situation in a given transaction where one party has more or better set of information than other. Such transaction may lead to market failure (Akerlof, 1970).

The most commonly used IPRs include patents, copyrights, trademarks, and trade secrets (Moschini, 2004; Edler et al, 2015). Therefore, the economics of IPRs lies in their role as legal tools enabling firms to realize the value of their investments in creation. However, critics argue that the enforcement of IPRs can lead to inflows of Foreign Direct Investment (FDI) and technology, reducing domestic competition, innovation, and capacity, thereby impeding long-term growth (Léger, 2006, 2007; Jin et al., 2013).

The TRIPS agreement of 1994 has led to IPR regimes globally. Questions have arisen regarding the impact of IPRs on economic growth (Maskus, 2000). IPRs are recognized as significant determinants of economic growth, mainly through incentivizing innovation (Gould and Gruben, 1996). Stronger IPRs are expected to positively affect growth and foster technical change *(*Maskus and McDaniel, 1999; Maskus, 2000*)*. For example, Coe et al. (1997) showed that a one-percent increase in imports of IPR-protected machines from OECD countries could raise Total Factor Productivity (TFP) in developing countries by around 0.03 percent. Similarly, stronger patents could increase TFP in China by 0.6 percent annually (Zhang and Shan, 2023). In addition, IPR legislation can spur FDI, contributing to growth, especially in developing countries (Park and Ginarte 1997; Staats and Biglaiser, 2012; Hsu and Tiao, 2015; Zhang and Yang, 2016). Intellectual property protection attracts investment, fosters entrepreneurship, creates new industries and jobs, and stimulates competition, all contributing to overall economic prosperity and social welfare. However, stringent IPR laws do not necessarily translate into high economic growth; their positive effects on growth are dependent on other factors facilitating growth, such as economic conditions and the country’s income level (Horii and Iwaisako, 2007; Adams, 2011; Sattar and Mahmood, 2011).

However, there is mixed evidence on the effect of IPRs on firm performance (Munari, 2013; Brem et al., 2017; Zhang and Shan, 2023). Nonetheless, the potential of IPRs to stimulate investment, innovation, and productivity remains critical for the growth of a nation in many significant ways.

Article 7 of the TRIPS agreement states that the main objective of IPRs is to promote both economic and social well-being. Hence, Intellectual Property protection not only contributes to growth but also has social implications (Lahsen and Piper, 2019). Some studies have examined the relationship between IPRs and well-being. IPRs protect the financial assets of individuals, creating a conducive environment for future investment and providing a sense of financial stability. Financial stability is an important measure of well-being (Bordo, 2007; Oishi et al., 2009; Green and Leeves 2013). Similarly, authors have linked freedom to make choices in life to positive impacts on welfare (Helliwell and Huang 2008; Helliwell et al., 2015). Along similar lines, Field (2007) suggests that property rights reduce the time spent protecting property, helping individuals dedicate time to other productive activities. Further, IPRs such as GIs can promote traditional agricultural goods by providing exclusive markets catering to consumers seeking safe and quality products willing to pay a premium price (Seetisarn and Chiaravutthi, 2011; Wirth, 2016; Mayasari, 2020). Such measures are likely to contribute to poverty alleviation, especially in rural areas (Jena and Grote, 2015; Lalitha and Vinayan, 2018). However, there are societal concerns regarding IPR legislation. IPR protection grants monopoly rights to inventors or producers, reducing competition and limiting output to socially desirable levels, resulting in welfare losses (Falvey et al., 2006). The debate on public health and IPR legislation highlights a serious social challenge. IPRs, such as patents held by pharmaceutical firms, have increased public health costs, making it difficult for people in developing countries to access medicines and technology (Sathwara and Bhandari, 2016). Therefore, despite the economic importance of IPRs, the significant social costs necessitate striking a balance for more equitable benefits.

There is a noticeable disparity in IPRs across countries, influenced by the reciprocal relationship between IPRs and economic development. Maskus (2000) argues that IPRs are endogenous, meaning national IPR regimes depend on the level of economic growth and vice versa. As a result, disparities in IPRs across countries are inevitable. According to a report by WIPO (2023), patent applications reached a record-breaking 3.5 million in 2022, nearly a 2% increase from 2021. Especially, China accounted for approximately 47% of these applications, followed by the US at 17% and Japan at 8%. Regarding trademarks, China filed approximately 48% of applications in 2022, with the US at 5% and India at 3%. For utility models, China's share was 98%, followed by Germany and the Russian Federation each at 0.3%. Over the past decade, Asia's global share of patents, trademarks, and industrial designs filings has significantly increased. Asia now accounts for almost two-thirds of global filings, demonstrating a shift in innovation geography from traditional leaders like the US, Japan, and EU countries to China and India (Godinho and Ferreira, 2011). Factors such as higher growth rates, increased investment in R&D, growth in FDI inflows, absorption of foreign technology and know-how, and industry orientation toward technological innovation have contributed to the growing presence of IPRs in these countries (Saxenian, 2006; Chandra et al., 2009; Hu and Jefferson, 2009). In short, country-specific characteristics and IPR growth are complementary, as demonstrated by the evolving IPR landscape in China and India.

A report jointly released by the Economic Research Department of the State Bank of India, Mumbai, and the Office of the Controller General of Patents, Designs & Trade Marks under the Department for Promotion of Industry and Internal Trade, Ministry of Commerce and Industry, Government of India, in 2024 (IPA, SBI Research, 2024) provides insight into India's intellectual property (IP) landscape. As the fifth-largest economy in the world, India ranked sixth globally in terms of the number of patents filed in 2022, marking significant growth from 42,854 patents in 2014 to 90,309 in 2023. The country is experiencing substantial innovation in emerging fields such as Computers, Communications, Biomedicals, and Polymers, underpinned by initiatives like Digital India. As a result, mechanical, chemical, electronics, electrical, and computer-related industries collectively account for over 60% of the top 15 sectors in IP innovation. India's robust push for innovation endeavours to promote a culture conducive to improving manufacturing performance and enhancing export competitiveness, with IPRs acting as a critical enabler (NITI Aayog, 2020).

The Trade-Related Aspects of Intellectual Property Rights (TRIPS) agreement, a multilateral framework under the World Trade Organization (WTO), encompasses seven key elements: Copyrights, Trademarks, Geographical Indications (GIs), Industrial Designs, Patents, Integrated Circuits Layout Designs, and Undisclosed Information and Trade Secrets. Geographical Indications designate goods as originating from a specific member country, where a certain quality, reputation, or characteristic of the product is essentially linked to its geographical origin. GIs are typically represented by popular place names that indicate the geographic source of goods and are prevalent worldwide, with a majority registered by China and European countries (Folkeson, 2005; WIPO, 2023).

The economic rationale behind GIs highlights the benefits derived from protecting goods associated with specific regions or places. These benefits include securing exclusive market access, commanding premium prices, enhancing job creation, improving worker welfare, promoting rural tourism, and stimulating the rural economy (Bramley et al., 2007; Rangnekar, 2004). Furthermore, products with high reputations face significant risks of counterfeit exploitation by competitors. GI tags play a crucial role in combating such counterfeiting practices, ensuring consumers are supplied with authentic products (Pai and Singla, 2016; Melini and Melini, 2019). Therefore, GI protection not only signals the quality and reputation tied to the place of production but also legally empowers producers to invest in enhancing the quality and reputation of their products based on their geographic origin.

India has established *sui generis* laws to introduce GIs, led by the Geographical Indications of Goods (Registration and Protection) Act, 1999, and complemented by the Geographical Indications of Goods (Registration and Protection) Rules, 2002 (GI Rules). These legislative efforts are seen as promoting rural and traditional knowledge-based industries across India. Over time and across various states, there has been a surge in GI registrations (see Figures 1.2 and 1.3). Handicrafts have dominated these registrations since the enactment of these laws, indicating their significant role in India's economy, which employs over 10 million people and engages in the production of over 35,000 products[6]. Recently, agricultural goods have also shown a growing trend in registration (Nanda et al., 2003). The registration of GIs for these products aims to safeguard their brand names from misuse, as seen with products like Darjeeling tea, Basmati rice, and Kashmir Pashmina Shawls, thereby protecting these industries from economic losses due to imitation.

[6] www.investindia.gov.in

The review of available literature highlights empirical investigations into the impact of Geographical Indication (GI) protection both within and outside India. Studies reveal significant sales growth in agricultural products and foodstuffs under European Protected Designations of Origin (PDO), averaging 5-10% annually, with exports accounting for nearly 20% of their total value (Correa, 2002; Pinna, 2002). Moreover, there is evidence indicating a positive increase in prices of GI-labeled goods (Loureiro and McCluskey, 2000; Hassan and Monier-Dilhan, 2002; 2006). Research by Jena and Grote (2015) underscores the positive impact of GI on labor welfare in India and Thailand, while other studies largely focus on its effect on product differentiation and pricing strategy. Importantly, producers of GI-designated products often command higher prices relative to non-GI counterparts due to the associated "collective reputation" or perceived higher quality (Pinna, 2002; EUROPA, 2003; Kaplinsky and Fitter, 2004; Lewin et al.; Teuber, 2010; Diallo, 2017) which influences consumers' willingness to pay (Landon and Smith, 1997; Fotopoulos and Krystallis, 2010). Furthermore, GIs, including PDOs, tend to positively impact employment due to their high workforce intensity, as highlighted by Barjolle (2016). They also contribute to rural tourism, income enhancement, and retention of rural populations, thereby bolstering rural employment and economies (Vital, 1999; Ploeg et al., 2000). In addition, GIs are instrumental in attracting investments (Blakeney, 2001; Barrera, 2020) and require producers to invest in brand-building to stimulate product quality perception among consumers (Bramley et al., 2009; Van Caenegem et al., 2014).

However, despite these benefits, studies indicate that the impact of GIs on prices and welfare is not uniformly positive (Loureiro and McCluskey, 2000; World Trade Report, 2004; ETEPS, 2006). This discrepancy is significant given that the main rationale for GI legislation often centers on enhancing welfare and territorial development (Pacciani et al., 2001; Bramley et al., 2007; Pike, 2015). Methodological differences and a lack of clear understanding contribute to inconclusive evidence on the overall effects of GIs (Teuber and Anders, 2011). Importantly, there remains a notable gap in economic investigations into the effects of GIs specifically in the context of India and Asia, a gap this study aims to address.

India holds a prominent position in global tea production, ranking as the second-largest producer after China and contributing significantly to global tea exports (Tea Board of India; IBEF, 2022). The tea plantation sector, largely rural-based in India, supports millions of livelihoods in economically disadvantaged regions of Northeast India, Kerala, Karnataka, and Tamil Nadu. The industry plays a crucial role in employment generation, particularly among rural and marginalized people, adhering to India's goals of equitable job distribution and income equality (Nagaraj, 2000; Kannan, 2009). Further, India's tea industry serves as a vital source of foreign exchange through exports to countries such as Russia, Iran, UAE, US, UK, Germany, and China (Tea Board of India; Chang and Brattlof, 2015).

The Tea Board of India (TBI)[7] holds proprietary rights over all Indian GI teas, covering Darjeeling tea, Kangra tea, Assam (orthodox) tea, Nilgiri (orthodox) tea, and Uttarakhand Berinag Tea. These teas derive their quality and reputation from their unique geographical attributes, making them exclusive to their respective regions (TBI). Legal protection for these Indian tea brands became essential due to widespread misuse by other players in the market seeking economic gains by falsely

[7] All tea grown in India is regulated by the Tea Board of India under the Tea Act of 1953.

labeling their teas as Darjeeling or Assam tea.[8] This study aims to examine the performance of these GI-registered teas compared to non-GI teas in the market.

1.3 Research Gaps

Despite numerous studies examining the impact of IPR laws on growth, the empirical literature remains limited, especially in the context of developing countries (Rangnekar, 2004). A significant challenge in these regions is the lack of adequate data, which has hindered research and resulted in a limited number of studies on the subject. Most existing literature focuses on Europe (Dias and Mendes, 2018), where data availability permits empirical investigation. However, firm-level studies on IPR impacts in Asia, including India, are significantly lacking. We may observe significant variations in the impact of GIs between European and Asian countries due to differing influences on firm performance.

Importantly, there is a dearth of firm-level research on the Indian tea industry, and studies addressing the impact of GIs on this sector are almost non-existent. The difficulties in data collection and the novelty of the issue contribute to this sparse literature.

Given the heterogeneous evidence of GIs, primarily from European contexts (Bowen and Zapata, 2009; Agostino and Trivieri, 2014; De Filippis et al., 2022), it is crucial to

[8] The annual sales of Darjeeling tea are around 40 million kgs, whereas the actual production hovers around 10 million kg. This shows that other teas, not originating from Darjeeling, are falsely branded as Darjeeling tea to extract its reputational benefits (Lecoent et al., 2010). Even teas from Sri Lanka, Kenya, and Nepal are sold as Darjeeling tea (Dasgupta, 1987; Lecoent et al., 2010). Shockingly, around 80% of the Darjeeling tea sold globally is counterfeit, mostly originated from Kenya, Sri Lanka, and even Nepal (Rangnekar, 2004; Lecoent et al., 2010). This widespread distortion makes Darjeeling Tea one of the most misused brands in the world. The practice of 'free-ride' and 'passing-off' of goods not only misleads consumers but also damages the hard-earned reputation of Darjeeling tea, which is built on it historical quality (Landon and Smith, 1997). A prime example of this issue could be teas and labelled as "Darjeeling tea made in Ceylon".

examine the effect of GIs on the Indian tea industry at various levels – firm, garden, and worker. This comprehensive approach will provide a deeper understanding of the implications of GI laws.

1.4 Objectives of the study

The main objectives of the study are:

1. To analyze the size, structure, and growth trends of the Indian tea industry relative to the F&B and manufacturing sectors

2. To examine the impact of Geographical Indications (GIs) on firm performance

3. To assess the role of GIs in influencing the wage gap between GI and non-GI (NGI) tea firms

4. To understand the employment effect of GIs on tea garden employment

5. To investigate the welfare outcomes for workers in GI tea gardens in Darjeeling

1.5 Data and Methodology

1.5.1 Data

The study utilizes both secondary and primary data sources. For secondary data, it heavily relies on the Annual Survey of Industries (ASI) data provided by the Central Statistical Office (CSO) of the Ministry of Statistics and Programme Implementation (MoSPI), Government of India. Data on firms involved in the processing and blending of tea from 1999-2000 to 2008-2009 are used for analysis. Additionally, garden-level data from the Regional Labour Offices, Government of West Bengal, conducted in 2011-12, is utilized. To address gaps in secondary data, a primary survey was conducted in 2023 in the Darjeeling district of West Bengal, covering 10 tea gardens, to understand the welfare of tea garden workers. Chapter 2 provides a detailed discussion of the data sources and their construction.

1.5.2 Methods

Various statistical tools and econometric techniques have been employed to investigate the effects of Geographical Indications (GIs). Ratios and growth rates are calculated to understand trends in the tea industry relative to the Food & Beverage (F&B) industry and manufacturing sector. Propensity Score Matching - Difference-in-Difference (PSM-DID) is used to measure the impact of GIs on firm performance. The Oaxaca Decomposition and Recentered Influence Functions (RIF)-Oaxaca Decomposition are applied to understand wage disparities and the factors explaining such disparities. Employment differences between GI and non-GI gardens are analyzed using Endogenous Treatment Regression (ETR) and Exogenous Switching Regression (ESR) models. The heterogeneous effects of GI employment on workers' welfare are captured using Instrumental Variable Treatment Regression (IVTR) and Unconditional Quantile Regression (UQR). Detailed discussions of these methods are provided in their respective chapters.

1.6 Contribution of the Study

This study significantly contributes to the literature by examining the implications of Geographical Indications (GIs) and addressing their presumed benefits. It expands the limited empirical research on GIs and firm performance in developing country contexts, exclusively focusing on multiple dimensions — firms, gardens, and workers. By utilizing comprehensive data at these levels, including rare insights from tea gardens and worker perspectives, the study offers valuable insights into the varied impacts of GIs. This multi-level approach not only enhances our understanding of how Geographical Indications (GIs) affect various groups but also offers practical advice for policymakers, industry experts, and stakeholders interested in promoting sustainable development through GI protection.

Three contributions are worth highlighting:

First, the study utilizes unique firm-level data to investigate the impact of Geographical Indications (GIs) on the Indian tea industry. Drawing from the Annual Survey of Industries (ASI) provided by the Ministry of Statistics and Programme Implementation (MoSPI), Government of India, we conduct a detailed analysis of how GIs have influenced firm performance and impacted wage inequality within the industry.

Second, our research elucidates the employment impacts of GIs, aimed at boosting rural employment and livelihoods. Given that tea gardens are central to rural economies, our findings offer crucial insights for policymakers, industry experts, and relevant authorities in shaping GI policy and strategic decisions.

Third, GIs are expected to enhance worker welfare. Utilising primary data, we analyse the welfare impacts of GI protection, particularly addressing the dismal living conditions of garden workers – an essential economic and social concern for both the industry and the state. Our study highlights crucial issues relating to the well-being of garden workers.

1.7 Organisation of the Study

This thesis is organized into eight chapters. The first chapter, Introduction, introduces the research problem from a broader perspective, critically analyzes the literature, identifies research gaps, sets the objectives, and outlines the novelty of the study. The second chapter, Data and Methods, explains the data sources, variables, and methods used in the study. The third chapter, Indian Tea Industry: Size, Structure, and Growth, highlights the overall performance of the tea industry compared to the Food & Beverage (F&B) sector and manufacturing. The fourth chapter, GI and Firm Performance, examines the link between Geographical Indications (GIs) and firm performance. The fifth chapter, GI and Wage Implications, decomposes the wage gap between GI and Non-GI (NGI) tea firms and identifies the factors that explain this wage gap. The sixth chapter, Employment Impact of GI Adoption, measures the impact of GI on garden employment levels. The seventh chapter, GI and Welfare Outcomes, focuses on the welfare aspects of tea workers in relation to GI intervention, specifically looking at consumption expenditure to capture the welfare consequences of GI adoption. The final chapter, Conclusions and Policy Implications, summarizes the study and offers policy implications. This chapter also highlights the limitations of the study and suggests new avenues for future research.

CHAPTER 2

DATA AND METHODS

2.1 Introduction

This chapter discusses the data sources and methods employed in the study. The study utilises both secondary and primary data to address its objectives across firm, garden, and worker levels. While the firm level and garden level data were sourced from secondary sources, worker-level data were collected through fieldwork. The chapter begins by discussing the secondary data sources for firm and garden-level information, including other sources used for district and state-level correlates. It then moves to a discussion on primary survey data, explaining the data collection strategy. Each section also sheds light on the data cleaning procedure adopted to arrive at the final working sample. Additionally, this chapter provides an overview of the methods employed to address the objectives of the study.

The rest of the chapter proceeds as follows: Section 2.2 presents a detailed discussion on the secondary data, including firm-level and garden-level datasets, and illustrates the steps taken for data cleaning and processing. Section 2.3 discusses the sampling strategy and execution of primary data collection, while Section 2.4 describes specific analytical methods used. The chapter concludes with a summary in Section 2.5.

2.2 Secondary Data Sources

2.2.1 Firm Level Data

For firm-level data on the Indian tea industry, we relied on the Annual Survey of Industries (ASI) data available on the official website of the Ministry of Statistics and Programme Implementation[9], Government of India. The ASI is the most comprehensive database on organized sector firms in the Indian manufacturing sector, covering nearly all large formal manufacturing establishments in the country. The survey is conducted annually by the Central Statistical Organisation (CSO) under the statutory provisions of the Collection of Statistics Act, 2008, and the rules framed thereunder in 2011. In the State of Jammu & Kashmir, it is conducted under the State Collection of Statistics Act, 1961, and the rules framed thereunder in 1964[10] (Chandrasekhar, 2005; ASI, 2020-21). The primary unit for data collection is a factory, based on a questionnaire filled out by the factories. The survey collects information on 'registered' or formal firms as per Sections 2m(i) and 2m(ii) of the Factories Act, 1948.[11]

The ASI frame is based on lists of registered factories maintained by the Chief Inspector of Factories in each state and registration authorities for bidi and cigar establishments and electricity undertakings. This frame is revised periodically by the Regional Offices of the Field Operations Division of NSSO in consultation with the Chief Inspector of Factories in the states[12] (Kapoor and Krishnapriya, 2017; Jayadev and Narayan, 2018). In line with Section 2m(i) and 2m(ii) of the Factories Act, only

[9] https://www.mospi.gov.in/
[10] https://www.mospi.gov.in/annual-survey-industries
[11] The ASI covers factories employing 10 or more workers using power, and those employing 20 or more workers without using power. It also includes bidi and cigar manufacturing establishments registered under the Bidi & Cigar Workers (Conditions of Employment) Act, 1966, with similar coverage (mospi.gov.in).
[12] mospi.gov.in/annual-survey-industries

units employing 10 or more workers with power or 20 or more without power are included in the frame. Factories are classified into two sectors: the census sector and the sample sector. Factories employing 100 or more workers fall under the census sector and are surveyed on a complete enumeration basis every year (ASI, 2013). The remaining factories are covered under the sample sector, where a representative sample is surveyed using a well-designed sampling procedure. A unit in the sample sector may or may not be surveyed in consecutive years. Importantly, ASI employs an effective mechanism for data collection, controlling for sampling errors associated with survey-based estimates (Manna, 2010).

We used repeated cross-sectional data from the period 1999-2000 to 2008-2009. This timeframe was chosen due to the availability of datasets with district identifiers, which are crucial for classifying firms into GI and Non-GI based on their location. However, ASI data with district identifiers is available only up to 2008-09. We relied on ASI for firm-level data as tea garden (plant) level data is not publicly available for longer periods, particularly those covering both pre- and post-GI implementation.

The ASI disaggregated industry-level data at the five-digit level for the period 1999-2000 to 2008-2009 was used in the study. During this period, three different national industrial classifications (NIC) were considered: NIC-1998 for surveys from 1998-99 to 2003-04, NIC-2004 for 2004-05 to 2007-08, and NIC-2008 from 2008-09 onwards. We used NIC-1998, NIC-2004, and NIC-2008 at the five-digit level to identify firms involved in the processing and blending of tea. We observed a change in NIC codes for tea firms at the five-digit level during the period of our study. These tea firms were coded as 15491 in NIC-1998 and NIC-2004, and 10791 in NIC-2008. Using these codes, we extracted data on firms engaged in the processing and blending of tea. The

ASI dataset provides comprehensive information on various aspects of a factory, including the year of establishment, ownership type, location, output, number of workers, employees, fixed capital stock, and wages. Detailed information on the variables used in the analysis and their construction is presented in Table 2.1.

Table 2.1 Construction of Variables

Variables	Definition
Number of Enterprises	Total number of enterprises
Employment	Total number of persons employed, including proprietors, owners and managerial staff
Output	Total ex-factory value of products and by-products manufactured as well as other receipts such as receipts from manufacturing and non-industrial services rendered to others.
Fixed capital stock	Fixed capital stock consists of land, buildings and other constructions, plant and machinery, transport equipment, tools, and other fixed assets that have a normal economic life of more than one year from the date of acquisition.
Wages	Wages include all regular monetary remuneration, such as direct wages, salaries, allowances, leave payments, and bonuses, but exclude lay-off payments (unless paid by the employer), social security contributions, and reimbursed business expenses.
Firm characteristics	
Location	Firms located in rural and urban locations.
Age	Firms are categorized as young and old based on median age value.
Ownership	Ownership type is categorized as public and private.

Note: The details about other variables used in the chapters have been discussed in the respective chapters.
Source: Own construction.

The ASI data is provided in ASCII format, requiring extraction using STATA software. The data is organised block-wise (Block A to J), with each block containing specific information about the factory.[13] After extracting each block, we merged them using a factory identifier (DSL) to compile a dataset for each year. We used a tabulation table specifying formulas for generating variables such as age, output, employment, and fixed capital stock. Subsequently, in STATA, we appended the datasets for each year to create a comprehensive dataset covering 1999-2000 to 2008-2009. For the tea industry analysis, we extracted units involved in the processing and blending of tea. In Chapter 3, we compare the performance of the tea industry relative to the Food and Beverages (F&B) industry and the entire manufacturing sector using the complete dataset. In Chapters 4 and 5, the analysis is confined to the tea industry alone, using a truncated dataset containing firms involved in the blending and processing of tea.

During our analysis, we encountered discrepancies in some extracted variables, indicating possible errors in reporting or data entry.[14] To address these discrepancies, such as negative values of fixed capital stock, output, and age, we followed established practices reported in the literature by dropping these observations from our analysis (Hasan and Jandoc, 2010; Dougherty et al., 2011; Jayadev and Narayan, 2018). Additionally, we retained only operational firms and excluded closed ones. These elimination criteria resulted in 5,557 operational tea manufacturing firms out of the original 5,935 in our dataset engaged in the processing and blending of tea (Table 2.2).

[13] https://microdata.gov.in/nada43/index.php/catalog/12
[14] For further details, see: https://mospi.gov.in/51-annual-survey-industries.

Table 2.2: Year-wise observations (ASI) of Firms Engaged in Tea Processing and Blending

Year	Total sample in the original data set (ASI)	Retained sample (ASI)	Retention (%)
2000	308	291	94.48
2001	619	603	97.42
2002	676	657	97.19
2003	747	708	94.78
2004	735	672	91.43
2005	634	576	90.85
2006	597	549	91.96
2007	569	525	92.27
2008	510	465	91.18
2009	540	511	94.63
Total	5935	5557	93.63

Note: We dropped all closed units
Source: Own estimates.

To ensure comparability over time, we used appropriate deflators to convert nominal values into real values. The Wholesale Price Index (WPI) and Consumer Price Index (CPI) served as our deflators. Output was deflated using the WPI for manufactured products at 2004-05 prices, fixed capital stock using the WPI for machinery and machine tools at 2004-05 prices, and wages using the CPI for industrial workers at 2004-05 prices.

During the period from 1999 to 2009, we standardised our comparisons by merging newly created states and districts with their parent districts. For example, districts like Bongaigaon, Barpeta, Kokrajhar, Baksa, Nalbari, Kamrup (including Kamrup Metro or Guwahati), Darrang, and Udalguri were treated as a single district within Assam. This consolidation was necessary due to the formation of Chirang district in 2004, which incorporated parts of Bongaigaon, Barpeta, and Kokrajhar. Similarly, Baksa district was formed in 2003 by merging parts of Nalbari, Barpeta, Kamrup, and Darrang. Likewise, we considered Bihar and Jharkhand as one state despite the creation of Jharkhand from Bihar in 2000. Similarly, Madhya Pradesh and Chhattisgarh were treated as a single state after Chhattisgarh was formed as a separate state from Madhya Pradesh in 2000. Additionally, Uttar Pradesh and Uttarakhand were also grouped as one state.

2.2.2 Garden Level Data

Chapter 6 utilises data from a 2011-12 survey conducted in the North Bengal tea-growing region of West Bengal, India. This survey, the first of its kind, was conducted by the Regional Labour Offices (RLOs) under the Joint Labour Commissioner of North Bengal Zone, Government of West Bengal. It covered Darjeeling Hills, Terai, and Dooars, including Darjeeling and Jalpaiguri districts. Data collection was managed by Assistant Labour Commissioner offices in Darjeeling, Kurseong, Kalimpong, Siliguri, Malbazar, Birpara, Jalpaiguri, and Alipurduar. The survey encompassed 273 gardens, and collected detailed information on various aspects such as workforce, production, finance, housing, health, wages, and retirement benefits. The data was sourced from the publication “Survey of Tea Gardens, 2013”. This dataset permits the precise classification of gardens into GI and NGI categories based on specific identifiers like garden names and locations.

2.2.3 Other Secondary Sources

Census of India

The Census of India provided essential demographic, social, and economic data used extensively in our analysis. Data from 2001, and 2011 were referred to for obtaining district and state-level information on population density, urbanization, literacy rates, and the distribution of scheduled tribe (ST) and scheduled caste (SC) populations. These variables were included as control variables in our analyses.

Reserve Bank of India (RBI)

We included district-level banking variables as control variables in our empirical analysis. Data on these variables for respective years were drawn from the RBI publication, "Basic Statistical Returns of Scheduled Commercial Banks in India". These reports provide comprehensive state-wise and district-wise data on branch offices, number of accounts, deposits, and outstanding credit of scheduled commercial banks, including Regional Rural Banks.

Google Earth

Google Earth provided valuable geographic data for our study, especially related to tea gardens in the Darjeeling district, West Bengal. We utilized Google Earth to gather elevation data (in meters above sea level) for these tea gardens. Additionally, it aided the measurement of distances (in kilometers) between the tea gardens and the main city of the Darjeeling district. Detailed discussion of these aspects is presented in Chapter 7, titled "GI and Welfare Outcomes".

2.3 Primary Survey

A primary survey was conducted in 2022-23 to assess the welfare of tea garden workers, focusing on income and consumption. The survey covered 10 selected tea gardens in the Darjeeling Hills and the Terai region of Darjeeling district. Using a structured questionnaire, we collected data from 200 workers employed in these gardens. The survey employed a stratified random sampling method to ensure fair representation across different strata of GI and NGI gardens, based on geographic location and GI certification. We selected five gardens from each stratum, considering specific garden characteristics such as size and age. We interviewed 20 randomly selected respondents from each garden Chapter 7, titled "GI and Welfare Outcomes", provides a detailed analysis based on the information gathered from these 200 workers.

We provide a concise summary of the data sources and methods employed in each empirical chapter in Table 2.3.

Table 2.3: Summary of Data and Methods Employed in Empirical Chapters

Chapters	Chapter Titles	Data source	Methods
Chapter 3	Indian Tea Industry: Size, Structure and Growth	ASI (Ministry of Statistics and Programme Implementation).	Descriptive statistics such as percentages and growth rates.
Chapter 4	GI and Firm Performance	ASI (Ministry of Statistics and Programme Implementation).	Propensity Score Matching-Difference-in-Difference (PSM-DID).
Chapter 5	GI and Wage Implications	ASI (Ministry of Statistics and Programme Implementation).	Oaxaca Decomposition and Recentered Influence Function-Oaxaca Decomposition.
Chapter 6	Employment Impact of GI Adoption	Survey of Tea Gardens, 2013, Government of West Bengal.	Endogenous Treatment Regression (ETR) and Exogenous Switching Regression (ESR).
Chapter 7	GI and Welfare Outcomes	Primary Survey, 2022-23.	Instrumental Variable Treatment Regression (IVTR) and Unconditional Quantile Regression (UQR).

Source: Own construction.

2.4 Method

The main objective of this study is to assess the impact of GI on the Indian tea industry. To achieve this objective, we employ a range of statistical tools and econometric techniques. In Chapter 3, we compared the growth trends and performance of the tea industry relative to the Food and Beverages (F&B) sector and the overall manufacturing sector using descriptive statistics such as percentages, ratios, and growth rates, with findings presented through charts and tables. For Chapters 4 through 7, we used advanced econometric methods to evaluate specific relationships. Chapter 4 employed the Propensity Score Matching - Difference-in-Difference (PSM-DID) method to capture the GI effect on firm performance. Chapter 5 analysed the wage gap using the standard Oaxaca Decomposition and Recentered Influence Functions (RIF)-Oaxaca Decomposition. Chapter 6 examined the employment implications of GI adoption using Endogenous Treatment Regression (ETR) and Exogenous Switching Regression (ESR) models. Finally, in Chapter 7, we explored the welfare effect of GI using Instrumental Variable Treatment Regression (IVTR) and estimated the heterogeneous effect of GI on workers' welfare using the Unconditional Quantile Regression (UQR) model. Detailed discussions of these methods are provided in the respective chapters.

2.5 Conclusion

This chapter provides an overview of the various data sources and methods utilized to address the objectives of the study. It includes a detailed discussion on the extraction and cleaning of ASI data from 1999-2000 to 2008-09, highlighting measurement issues and challenges faced in gathering data pertaining to the tea industry. The chapter also covers the garden-level data from the Regional Labour Offices, used to examine the employment implications of GI. To address gaps in secondary data, a primary survey was conducted, discussed in detail in this chapter along with an explanation of the sampling strategy employed to identify survey respondents. The chapter concludes with a brief discussion on the econometric methods employed to capture the GI effect. The following chapter presents a descriptive analysis of the size, structure, and growth of the tea industry.

CHAPTER 3

INDIAN TEA INDUSTRY: SIZE, STRUCTURE, AND GROWTH

3.1. Introduction

The Indian Tea Industry is the world's second-largest producer and fourth-largest exporter of tea, contributing over 23 percent of global tea production (Deka, 2018). It significantly impacts the nation's economy through output, employment, and exports. Known for its labour-intensive nature (Behal, 1985; Savur, 1973; ILO, 2016), the industry is a consistent source of rural livelihood and holds a notable share in the manufacturing sector (around 1 percent). This chapter examines performance trends and the industry's contribution to Indian manufacturing from 2000 to 2009, highlighting trends in enterprises, employment, fixed capital stock, output, and wages. It also examines how the performance varies by firm characteristics, and compares the tea industry's share in the Food and Beverage (F&B) industry and the overall manufacturing sector. The analysis is based on firm-level data from the Annual Survey of Industries for 2000-2009, as discussed in Chapter 2.

This chapter is organized as follows. Section 3.2 discusses the data and methods. Section 3.3 examines the size and growth of the tea industry relative to the F&B industry and the overall manufacturing sector from 2000 to 2009. The factor productivities are examined in section 3.4. Section 3.5 compares the size, growth, and productivity of GI and NGI firms in the tea industry. Section 3.6 provides concluding remarks.

3.2 Data, Variables and Methods

3.2.1 Data

The Chapter uses ASI firm-level data[15] from 2000-2009, contingent on the availability of district identifiers. These identifiers are crucial for classifying the firms as Geographical Indication (GI) or Non- Geographical Indication (NGI) based on their locations, as discussed in Section 3.5. We have collected ASI data on enterprises, employment, output, fixed capital stock, and wages to examine the objectives of the study. Chapter 2 on Data and Methods provides a detailed discussion on this ASI dataset. Below, we present a table on the construction of variables for our measurement.

3.2.2 Variables

Construction of Variables

The primary objective of this chapter is to document the performance trends of tea compared to F&B and overall manufacturing sectors from 2000 to 2009. This subsection discusses how we construct our measures of firm performance. Table 3.1 describes the variables used in our analysis.

[15] We use real values for output, fixed capital stock, and wages. For details, please refer to Chapter 2 on Data and Methods.

Table 3.1: Construction of Variables

Variables	Definition
Number of Enterprises	Total number of enterprises
Employment	Total number of persons employed, including proprietors, owners and managerial staff
Output	Total ex-factory value of products and by-products manufactured as well as other receipts such as receipts from manufacturing and non-industrial services rendered to others.
Fixed capital stock	Fixed capital stock consists of land, buildings and other constructions, plant and machinery, transport equipment, tools, and other fixed assets that have a normal economic life of more than one year from the date of acquisition.
Wages	Wages include all regular monetary remuneration, such as direct wages, salaries, allowances, leave payments, and bonuses, but exclude lay-off payments (unless paid by the employer), social security contributions, and reimbursed business expenses.
Firm characteristics	
Location	Firms located in rural and urban locations.
Age	Firms are categorized as young and old based on median age value.
Ownership	Ownership type is categorized as public and private.
Productivities	
Enterprise productivity	Ratio of output to number of enterprises.
Labour productivity	Ratio of output to employment.
Capital productivity	Ratio of output to capital.
Capital intensity	Ratio of fixed capital stock to employment.
Wage per employee	Ratio of wages to employment.

Source: Own construction.

The size, structure, and growth of the sector are examined using five indicators: the number of enterprises, employment, fixed capital stock, output and wages. The number of enterprises represents the total count of active enterprises operating in the sector. Employment refers to the total workforce engaged in these enterprises, including proprietors, owners, managerial staff, and employees. Output is the ex-factory value of goods produced and services rendered by the industry. Fixed capital stock comprises the durable assets owned by enterprises, including land, buildings, machinery, and equipment. Wages include all regular monetary compensation paid to employees, covering wages, salaries, allowances, and bonuses.

In this chapter, we also analyze trends in these variables across selected firm characteristics. Firm characteristics include location, distinguishing between rural and urban areas; age, categorizing firms as young or old based on their median age; and ownership, differentiating between public and private types. We also assess firm performance using selected factor ratios. Enterprise productivity, a proxy for firm efficiency, is measured as the ratio of output to the number of enterprises. Labor productivity, indicating workforce efficiency, is measured as the ratio of real gross output to the number of persons engaged. Capital productivity, capturing the effective use of capital, is computed as the ratio of output to capital. Capital intensity, reflecting the amount of fixed capital stock per worker, provides insights into capital investment per employee. Lastly, wage per employee, the average wage determined by dividing total wages by employment, measures compensation levels within firms.

3.2.3 Methods

The analysis in this chapter relies on descriptive statistics such as percentages, ratios, and growth rates, presented in figures and tables to compare the tea industry's performance with the F&B and manufacturing sectors. Average annual growth rates are computed as compound annual growth rates (CAGR). CAGR is calculated as $[(Y_t/Y_0^{(1/t)} - 1] * 100$, where Y_t and Y_0 are the terminal and initial values of the variable, and "t" is the time over which CAGR has to be calculated. Factor ratios are also computed to examine the trends in the productivity of the sector.

3.3 Size and Growth Trend

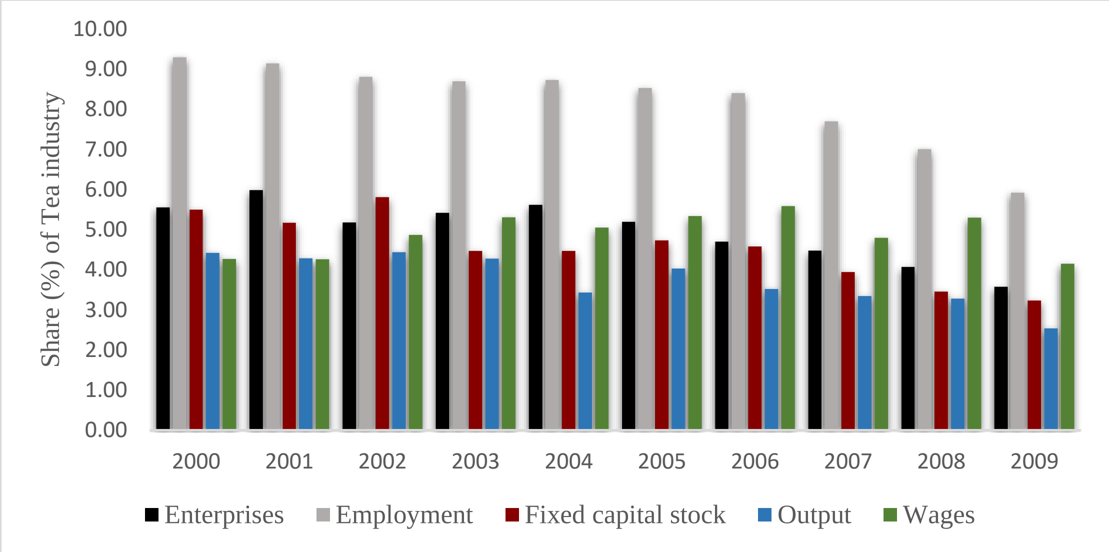
3.3.1 Size and Growth of the Tea Industry

This section examines the performance of the tea industry over time in the F&B and manufacturing sectors, using five indicators: number of firms, employment, fixed capital stock, output, and wages. We analyse changes and trends in the performance of the tea industry and compare it to that of the F&B and manufacturing sectors. Additionally, we examine how performance varies based on firm characteristics, such as location, ownership, and age.

During 2000-2009, the tea industry accounted for about 5 percent of the F&B sector and 1 percent of the manufacturing sector (Figures 3.1 and 3.2). Despite being a major employment provider, the number of workers declined from 125,000 in 2000 to 106,000 in 2009 (Table 3.2). The industry's share decreased from 9 percent to 6 percent in F&B and from 1.6 percent to 1.3 percent in manufacturing (Figures 3.1 and 3.2). Fixed capital stock, output, and wages in the tea industry also declined relative to F&B and manufacturing over the same period (Figures 3.1 and 3.2).

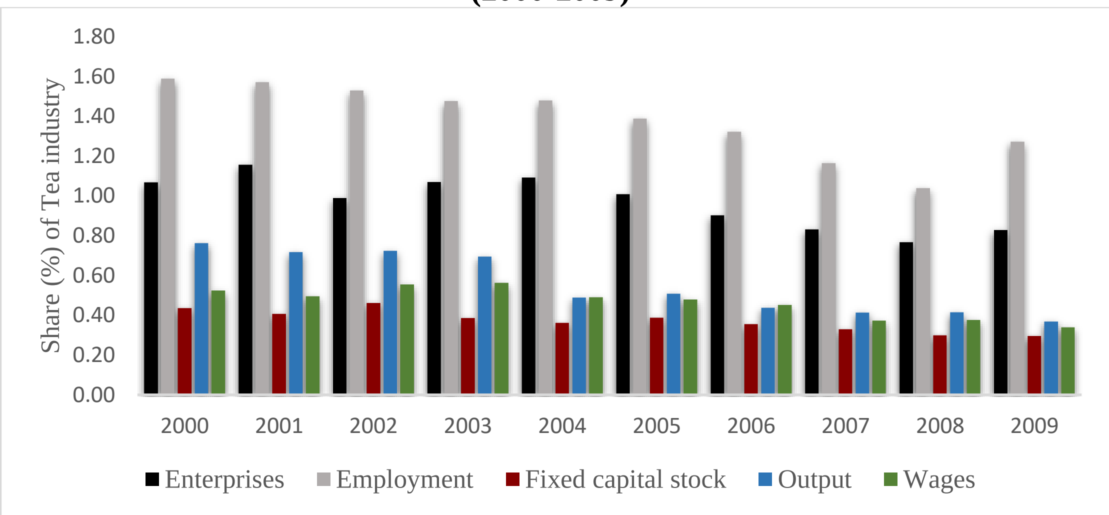
The tea industry experienced a negative growth rate of 2.21 percent per annum, while F&B grew at 2.19 percent and manufacturing at 0.31 percent (Table 3.2). Employment in the tea industry declined, whereas F&B employment increased by around 3 percent per annum. Fixed capital stock and output grew faster in F&B and manufacturing compared to the tea industry. The wage rate of manufacturing grew at twice the rate of wages in the tea and F&B sectors during this period. From 2005 onwards, the F&B and manufacturing sectors consistently outpaced the tea industry's growth (Figure 3.3). The next subsections (3.3.2 – 3.3.4) present trends by selected firm characteristics.

Figure 3.1: Tea Industry's Share (%) in Indian F&B Sector (2000-2009)



Source: Own estimates.

Figure 3.2: Tea Industry's Share (%) in Indian Manufacturing Sector (2000-2009)



Source: Own estimates.

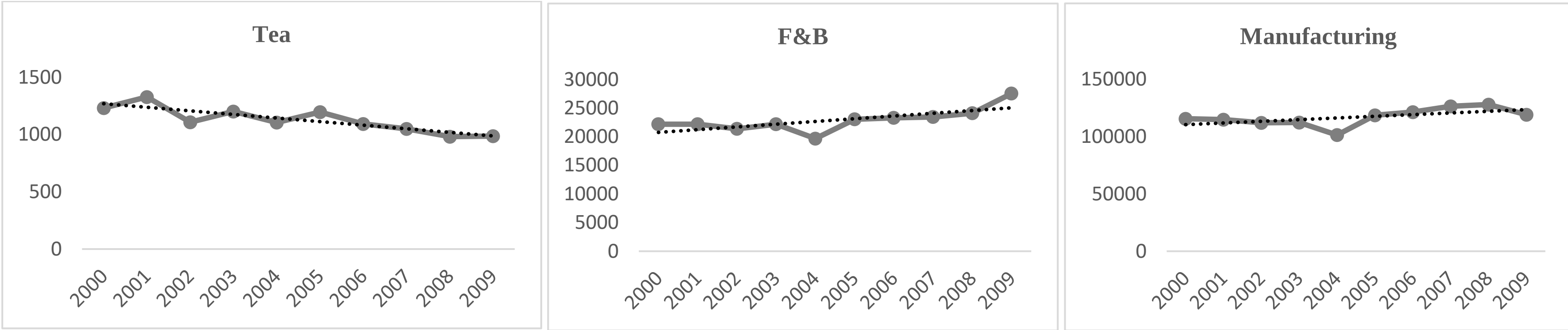
Table 3.2: Size and Structure of Tea Industry in F&B and Manufacturing Sectors (2000-2009)

	Number of Enterprises (in Thousand)										Growth (%)		
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**Growth**	**Growth (Pre GI)**	**Growth (Post GI)**
Tea	1.23	1.33	1.11	1.20	1.11	1.20	1.09	1.05	0.98	0.99	-2.21	-0.59	-4.73
F&B	22.19	22.18	21.39	22.16	19.68	23.03	23.28	23.46	24.10	27.55	2.19	0.74	4.58
Manufacturing	115.54	114.90	112.17	112.45	101.40	118.70	121.39	126.54	128.02	119.15	0.31	0.54	0.09
	Employment (in Lakhs)										**Growth**	**Growth (Pre GI)**	**Growth (Post GI)**
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**			
Tea	1.25	1.20	1.13	1.12	1.05	1.12	1.15	1.12	1.04	1.06	-1.64	-2.17	-1.37
F&B	13.44	13.12	12.82	12.87	12.02	13.13	13.68	14.54	14.83	17.90	2.91	-0.47	8.06
Manufacturing	78.73	76.43	73.91	75.89	70.98	80.77	87.03	96.18	100.17	83.33	0.57	0.51	0.79
	Fixed capital stock (Rs. in Billion)										**Growth**	**Growth (Pre GI)**	**Growth (Post GI)**
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**			
Tea	21.10	17.70	21.10	17.90	16.90	18.80	19.60	20.20	20.60	23.50	1.08	-2.28	5.74
F&B	383.40	342.30	363.80	399.80	377.50	397.20	428.50	511.80	594.80	727.70	6.62	0.71	16.34
Manufacturing	4847.60	4359.60	4582.00	4642.50	4680.10	4855.50	5530.20	6151.00	6892.70	7974.20	5.10	0.03	13.20
	Output (Rs. in Billion)										**Growth (Overall)**	**Growth (Pre GI)**	**Growth (Post GI)**
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**			
Tea	70.30	59.80	74.90	104.60	64.50	82.10	80.70	92.20	101.40	86.00	2.04	3.15	1.17
F&B	1589.80	1395.50	1685.20	2440.90	1876.20	2036.30	2289.40	2751.60	3088.20	3381.80	7.84	5.08	13.52
Manufacturing	9229.60	8350.40	10347.50	15064.10	13179.10	16162.10	18466.90	22335.90	24490.60	23357.80	9.73	11.86	9.64
	Wages (Rs. in Billion)										**Growth**	**Growth (Pre GI)**	**Growth (Post GI)**
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**			
Tea	2.30	2.32	2.60	2.90	2.50	2.90	2.60	3.00	3.70	3.50	4.29	4.75	4.81
F&B	53.90	54.60	53.60	54.20	50.30	53.50	46.60	63.40	69.10	84.20	4.56	-0.15	12.01
Manufacturing	440.60	469.90	471.90	511.30	517.90	596.30	577.10	817.50	973.60	1029.50	8.86	6.24	14.63

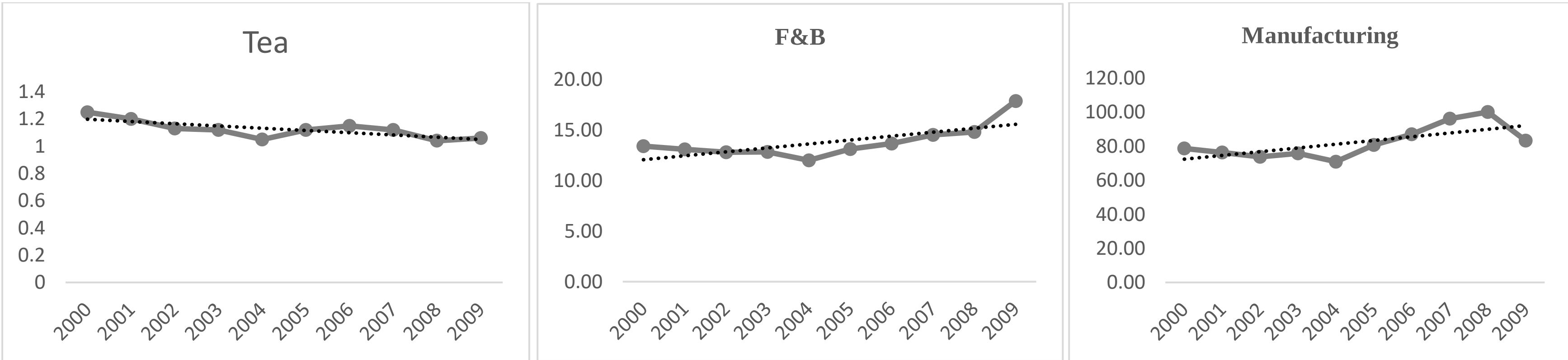
Notes: CAGR is a measure of growth. Overall incorporates the period 2000-2009. Pre-GI includes the period 2000-2005. Pre-GI includes the period 2000-2005.
Source: Own estimates.

Figure 3.3: Performance Trends: Tea, F&B, and Manufacturing Sectors (2000-2009)

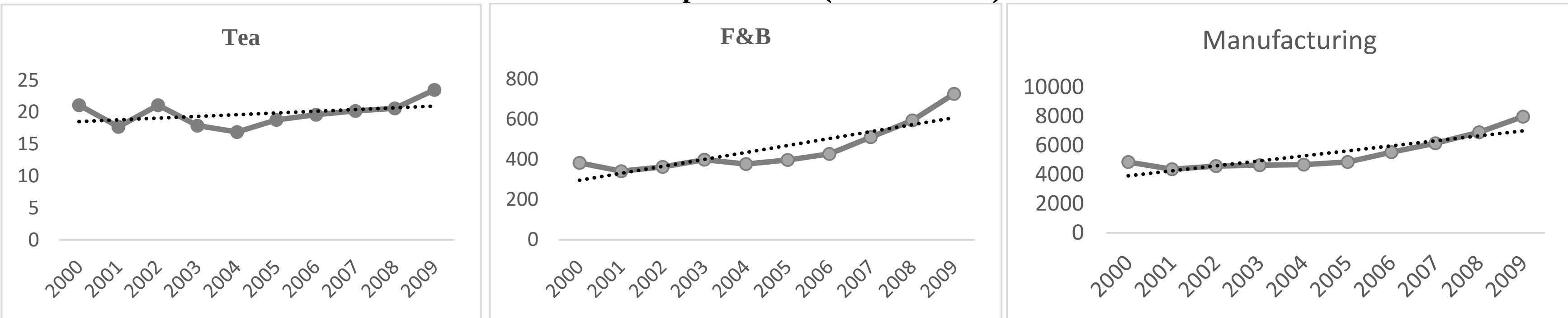
Number of Enterprises



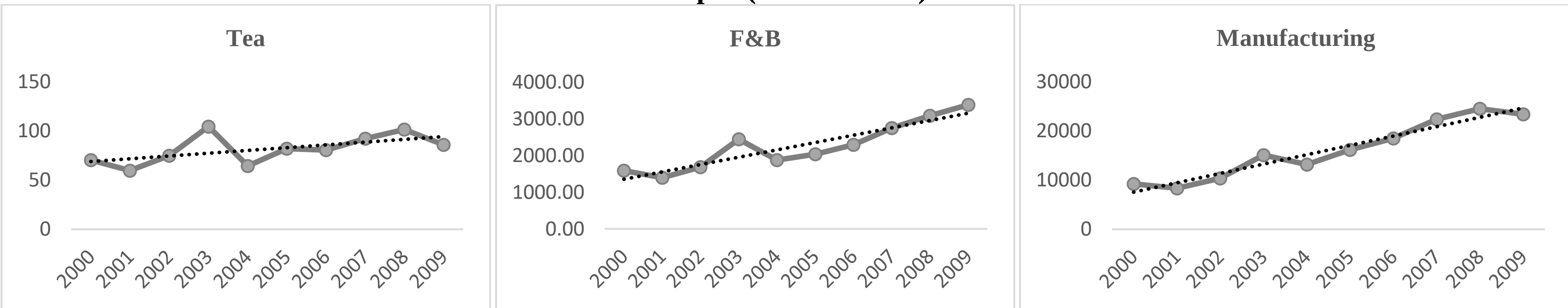
Employment (in lakhs)



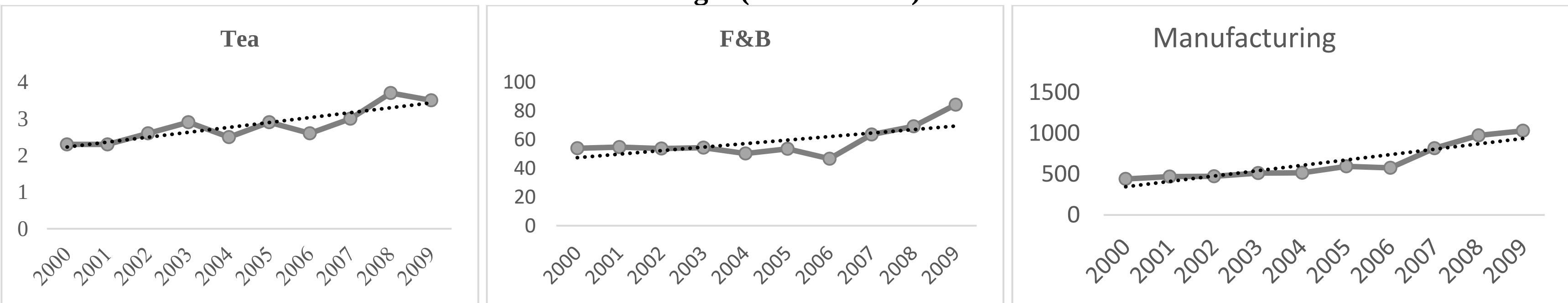
Fixed Capital Stock (Rs. in Billion)



Output (Rs. in Billion)



Wages (Rs. in Billion)



Source: Own estimates.

3.3.2 Trends by Location

Figures 3.5 and 3.6 show the share of the tea industry by location from 2000 to 2009, indicating its prevalence in rural areas. Rural tea firms dominate the industry, with their share declining marginally over time but remaining substantially higher than urban tea firms (Figures 3.4 and 3.5). Consequently, rural employment and fixed capital stock in the tea industry maintain a higher share compared to urban areas in F&B. This trend is also reflected in output and wages, where the rural share, despite declining, remains higher than that of urban tea firms.

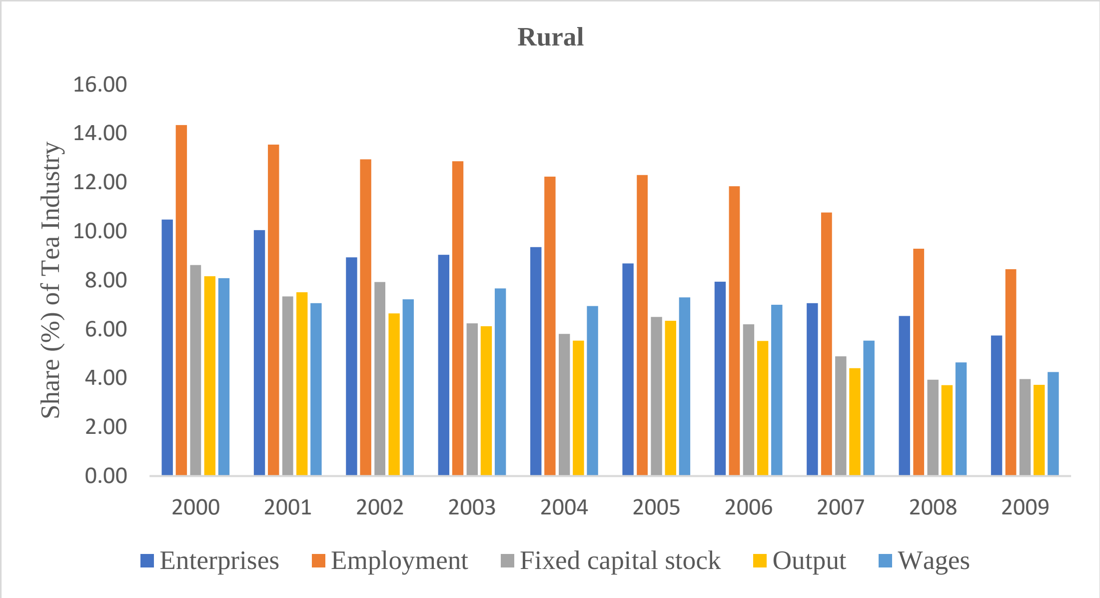
In manufacturing, rural tea firms also experienced a steady decline (Figure 3.6). Despite this, rural tea firms maintained a higher share than their urban counterparts in employment, fixed capital stock, and wages, highlighting the changing dynamics in both rural and urban settings.

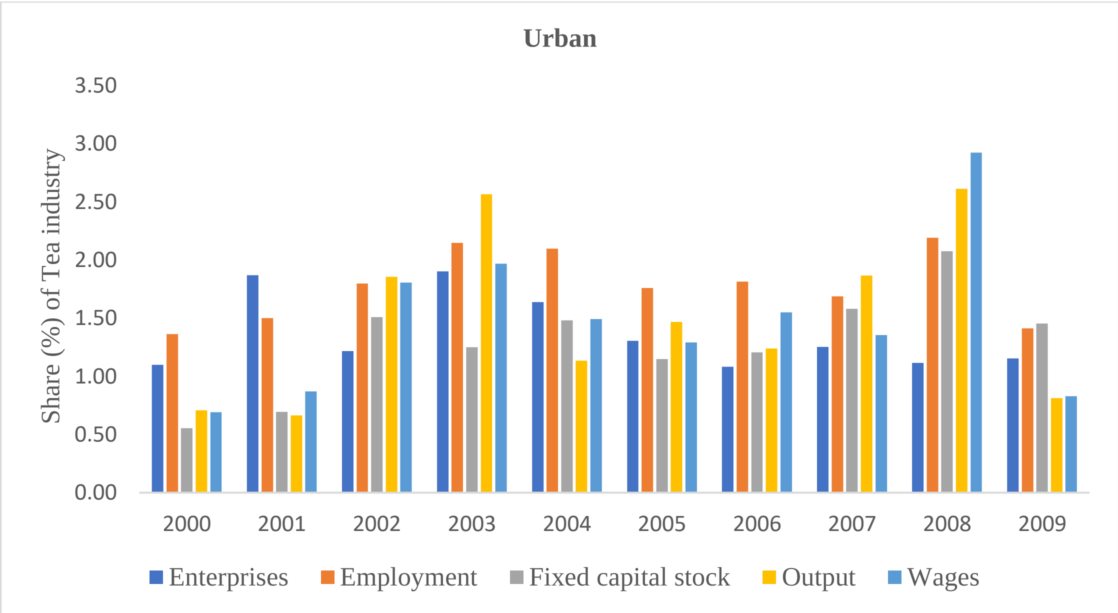
Overall, the share of rural tea firms compared to urban tea firms declined from 2000 to 2009. Urban tea firms gained a higher share in 2009 than in 2000, with a sharper decline among rural tea firms in F&B compared to manufacturing. The rural share in F&B declined by around 5-6 percent, while in manufacturing it saw a 1 percent decline. On the other hand, the rise in the share of urban tea firms was more pronounced in F&B compared to manufacturing, especially in fixed capital stock and wages. Despite the falling rural share in both F&B and manufacturing, their dominance remains substantial compared to urban tea firms.

Figure 3.4: Tea Industry Composition by Location

Source: Own estimates.

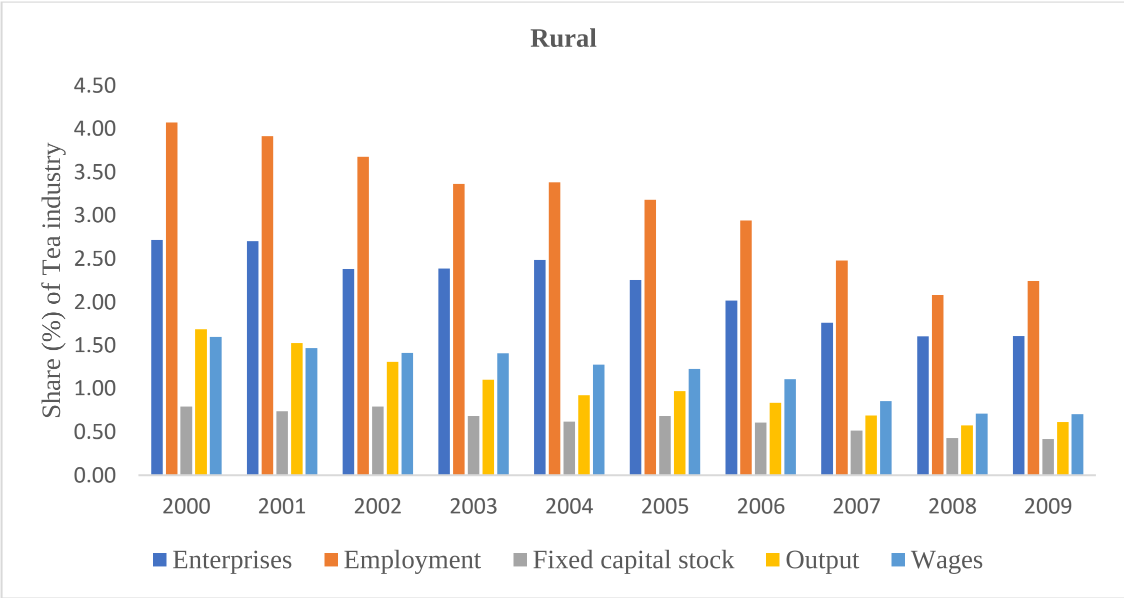
Figure 3.5: Share (%) of Tea Industry by Location in F&B

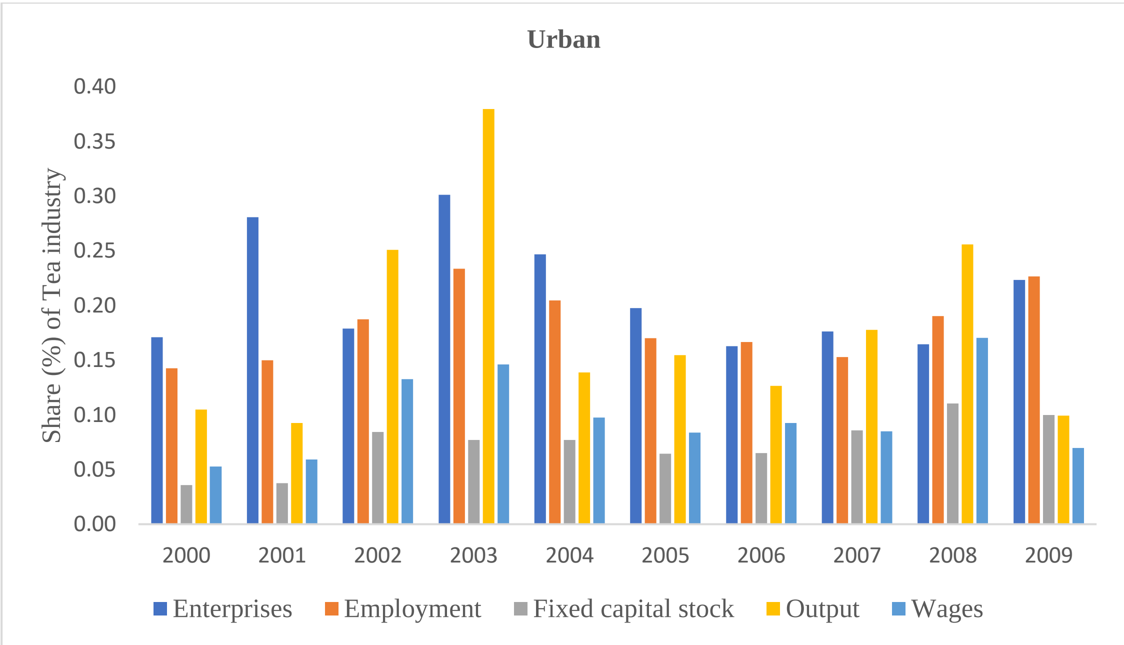




Source: Own estimates.

Figure 3.6: Share (%) of Tea Industry by Location in Manufacturing



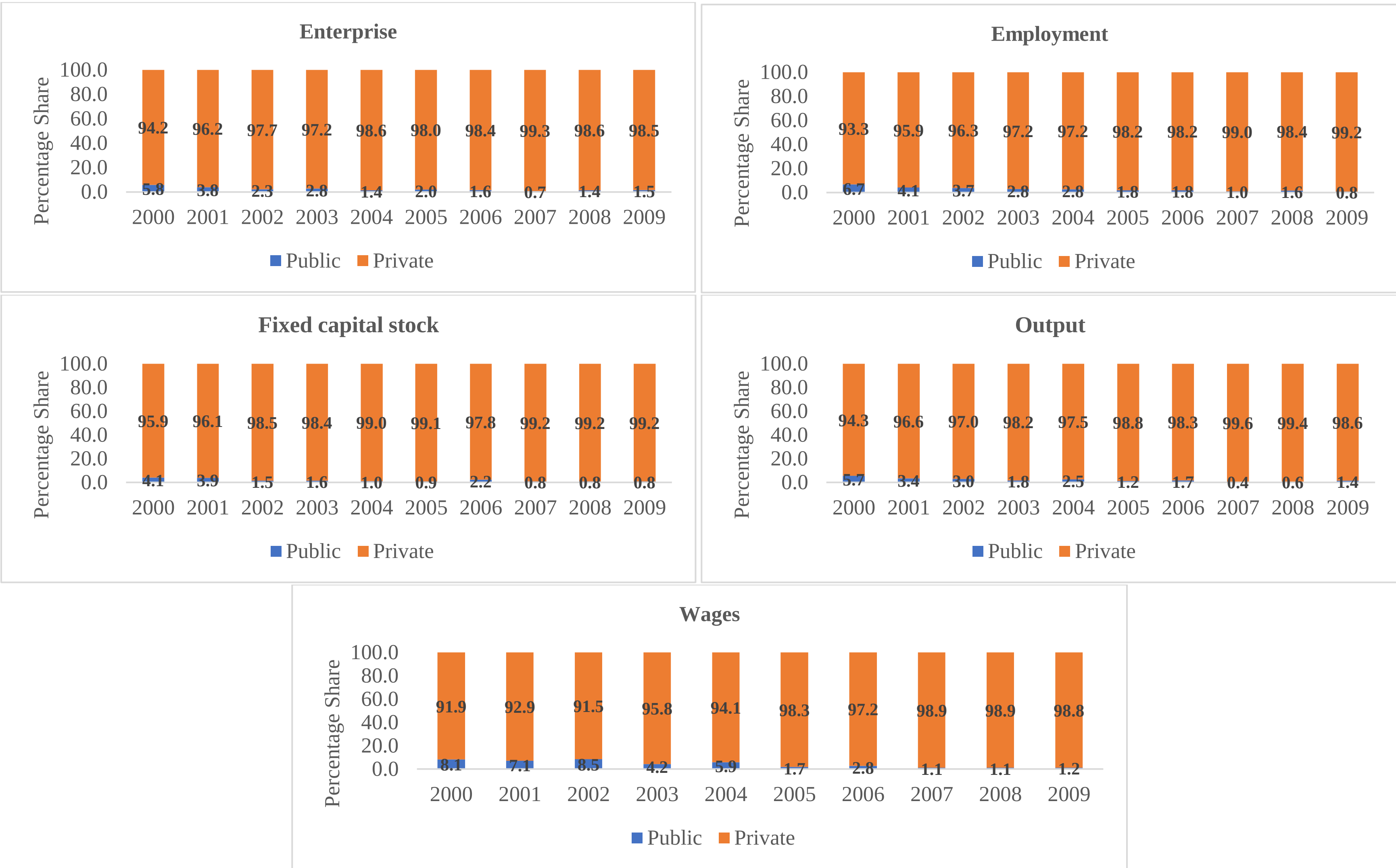


Source: Own estimates.

3.3.3 Trends by Ownership

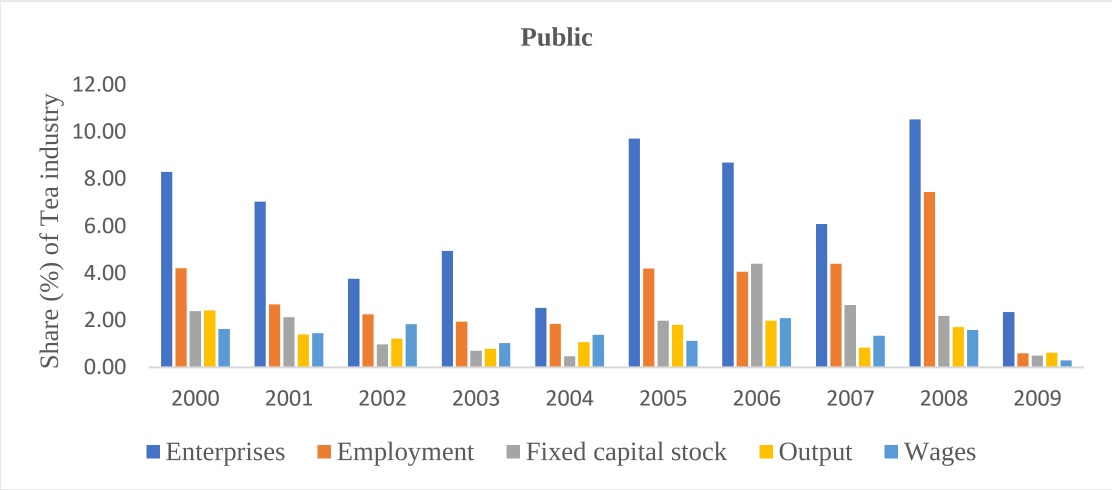
Next, we explore the prevalence of the tea industry across different ownership categories. Dividing firms into public and private ownership, we find variations in the incidence of tea firms by ownership (Figures 3.8 and 3.9). Private tea firms consistently hold over 90% of the share across all parameters compared to public firms (Figure 3.7). Both public and private tea firms witnessed a decline over time in both F&B and manufacturing, with this decline more pronounced in F&B and among public tea firms. A similar trend is discerned for employment, fixed capital stock, and output, with the fall in wages being higher for private tea firms than public firms in both F&B and manufacturing. This suggests a difference in the incidence of the tea industry based on ownership across F&B and manufacturing.

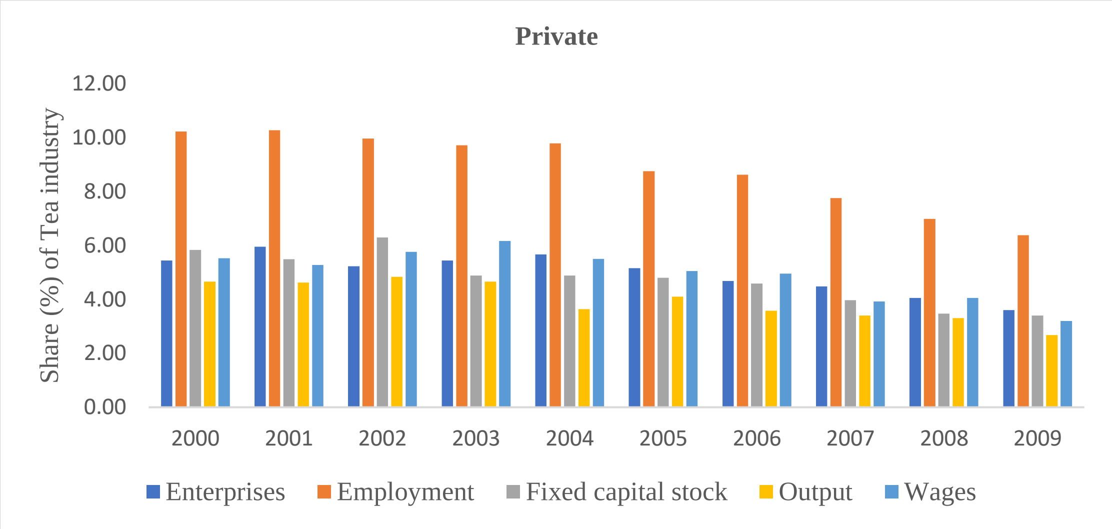
Figure 3.7: Tea Industry Composition by Ownership



Source: Own estimates.

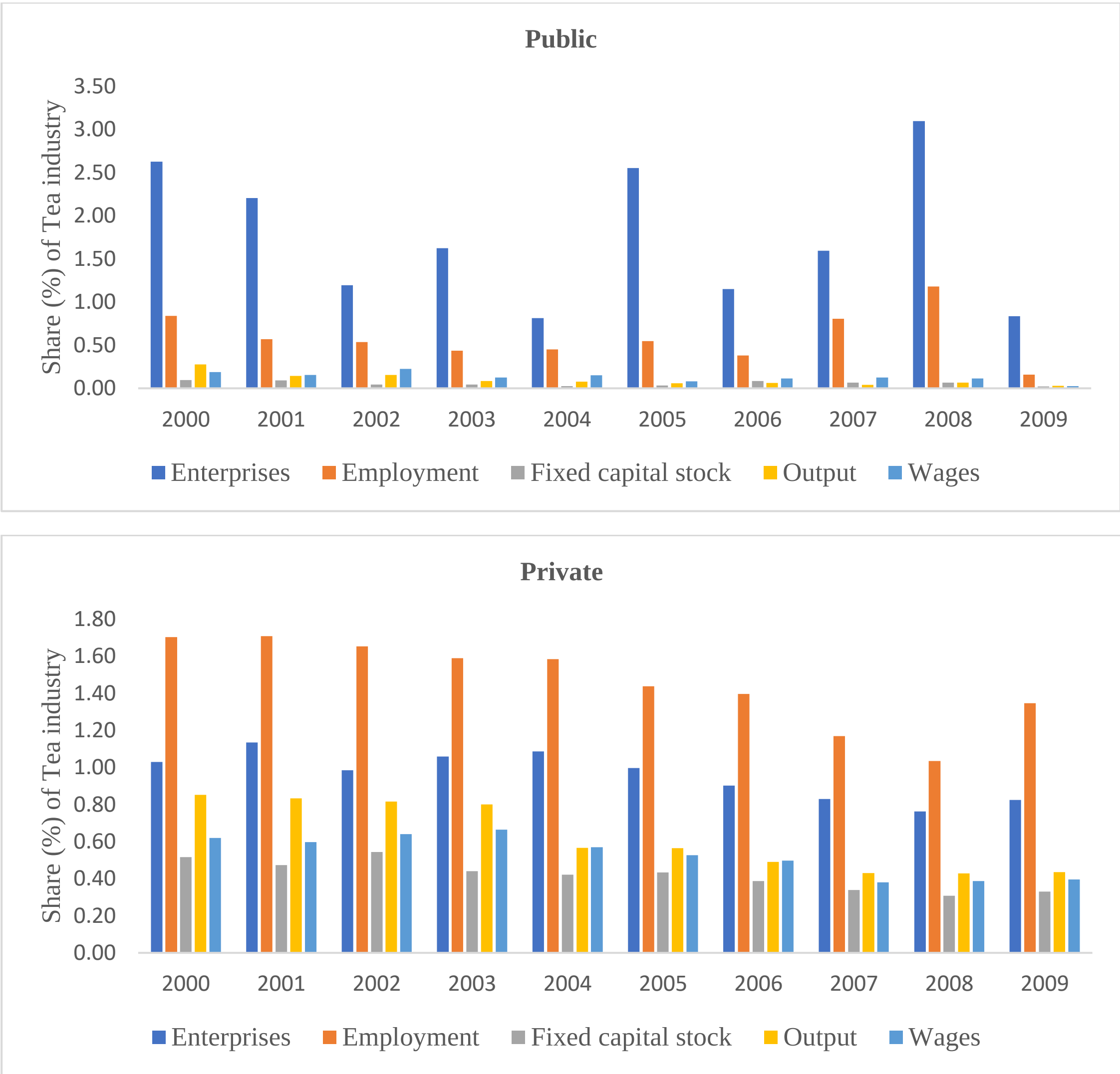
Figure 3.8: Share (%) of Tea Industry by Ownership in F&B





Source: Own estimates.

Figure 3.9: Share (%) of Tea Industry by Ownership in Manufacturing



Source: Own estimates.

3.3.4 Trends by Age

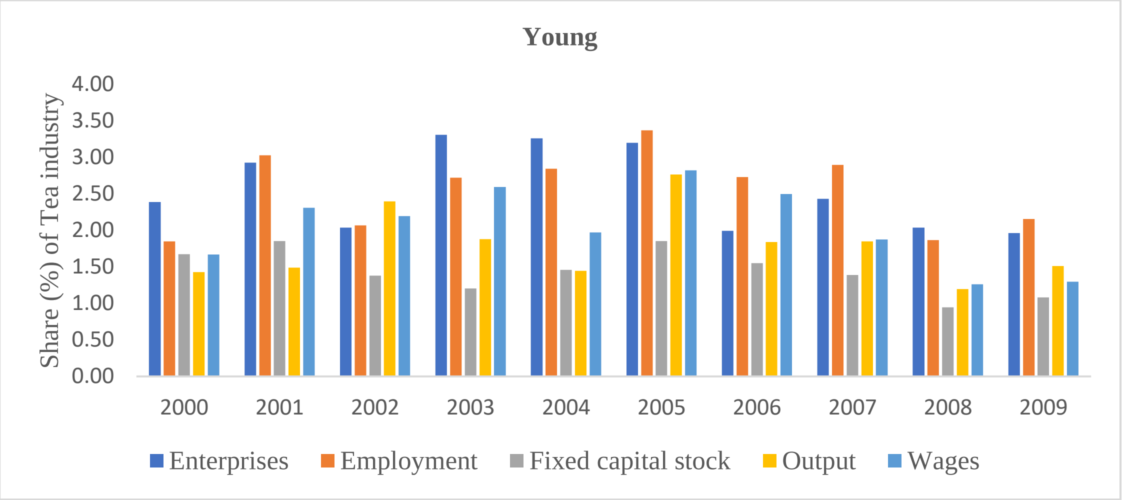
Figure 3.11 examines the incidence of the tea industry among younger and older firms, displaying its share in F&B and manufacturing by age of the firm. Firms are classified as young if their age is less than or equal to the median age, and old if their age exceeds the median. Over 80% of firms, employment, fixed capital stock, output, and wages are contributed by older tea firms, though the share of younger firms increased from 2000 to 2009 (Figure 3.10). Figures 3.11 and 3.12 capture variations in the incidence of the tea industry in F&B and manufacturing based on firm age. In

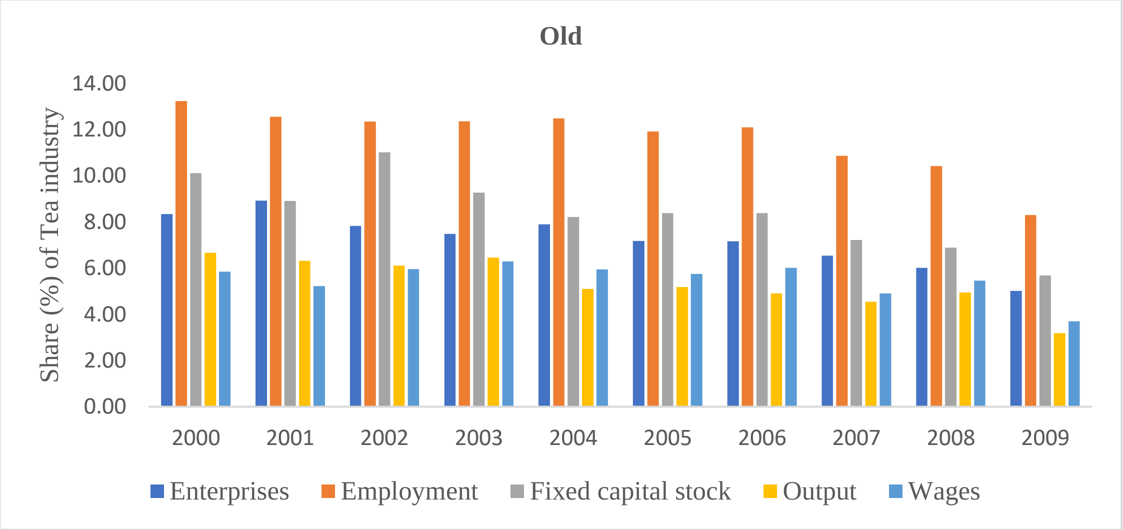
2009, old tea firms in F&B accounted for 5.02 percent of enterprises, 8.30 percent of employment, 5.69 percent of fixed capital stock, 3.18 percent of output, and 3.70 percent of wages, whereas young tea firms reported lower shares. In manufacturing, older tea firms accounted for 1.26 percent of enterprises, 1.88 percent of employment, 0.44 percent of fixed capital stock, 0.44 percent of output, and 0.43 percent of wages, with younger tea firms reporting lower incidences. Overall, the share of the tea industry in F&B and manufacturing varies by firm age.

Figure 3.10: Tea Industry Composition by Firm Age

Source: Own estimates

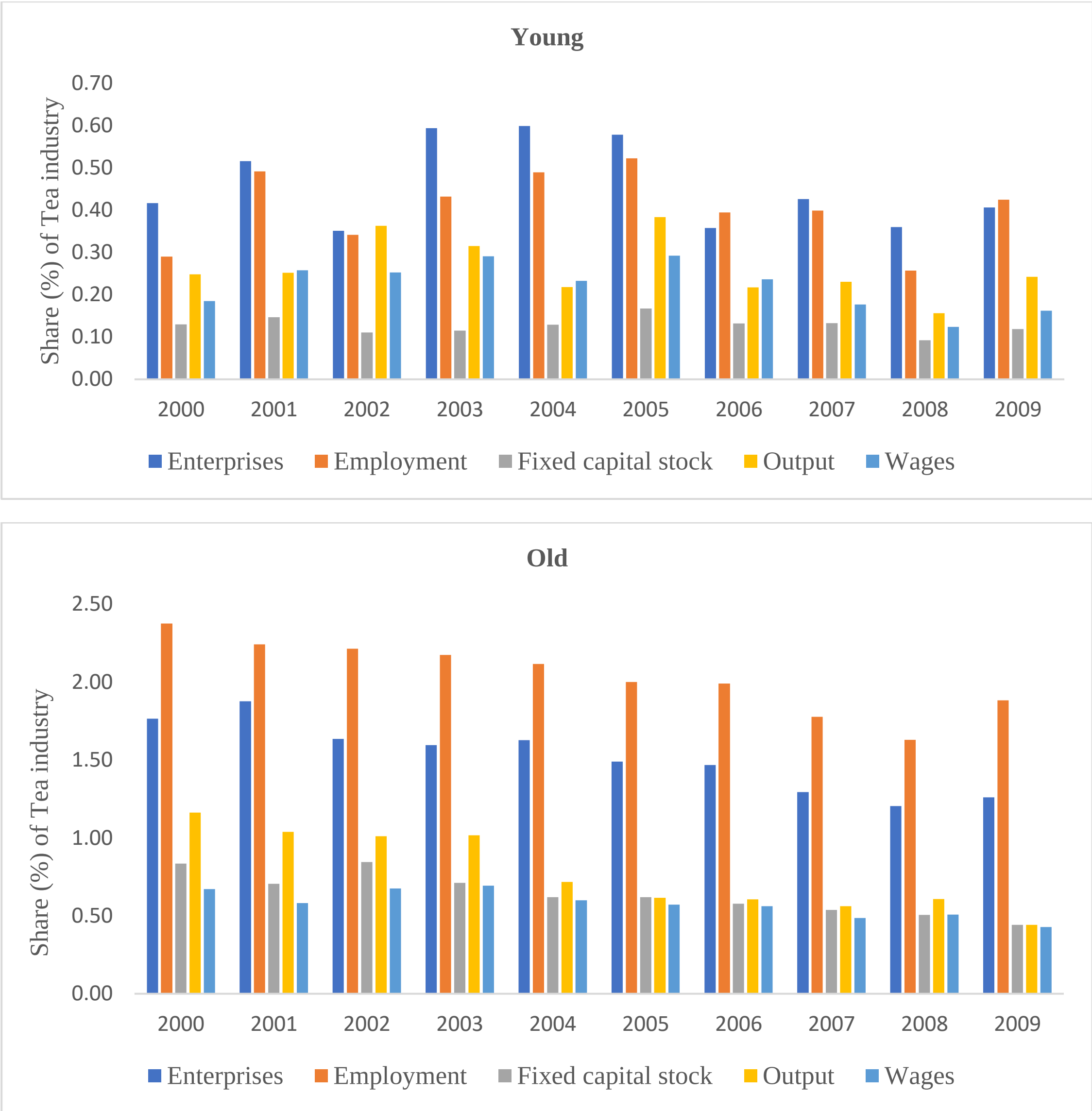
Figure 3.11: Share (%) of Tea industry by Age in F&B





Source: Own estimates.

Figure 3.12: Share (%) of Tea industry by Age in manufacturing



Source: Own estimates

3.4 Factor Ratios

This section focuses on the productivity performance of the tea industry, examining trends in enterprise productivity, labour productivity, capital intensity, and wages per employee (Table 3.3). The estimates indicate that the tea industry is less productive, with workers earning less compared to F&B and manufacturing. In 2009, tea enterprises were 1.5 times less productive and labour productivity was 2.33 times lower than in F&B. Compared to manufacturing, tea enterprises were about 2.25

times less productive, and labour productivity was 1.30 times lower. Additionally, capital productivity, capital intensity, and wages per employee were about 2 times lower than in the F&B sector in 2009. Notably, the productivity gap widened significantly between 2000 and 2009, along with an increase in earnings inequality (Table 3.3).

Table 3.3: Trends in Factor Ratios (2000 to 2009)

Year	**Tea**	**F&B**	**Manu**	**Productivity gap between***	
(1)	**(2)**	**(3)**	**(4)**	**(2) & (3)**	**(2) & (4)**
Enterprise Productivity	*(Rs. in million)*				
2000	57.04	71.64	79.88	14.60	22.84
2001	45.03	62.91	72.68	17.88	27.64
2002	67.56	78.77	92.25	11.21	24.69
2003	86.98	110.15	133.97	23.17	46.98
2004	58.28	95.34	129.97	37.05	71.68
2005	68.56	88.43	136.16	19.87	67.60
2006	73.74	98.36	152.13	24.61	78.39
2007	87.70	117.28	176.52	29.57	88.81
2008	103.24	128.14	191.31	24.90	88.07
2009	87.19	122.76	196.05	35.57	108.85
Labour productivity	*(Rs. in million)*				
2000	0.56	1.18	1.17	0.62	0.61
2001	0.50	1.06	1.09	0.57	0.60
2002	0.66	1.31	1.40	0.65	0.74
2003	0.93	1.90	1.98	0.97	1.05
2004	0.61	1.56	1.86	0.95	1.24
2005	0.73	1.55	2.00	0.82	1.27
2006	0.70	1.67	2.12	0.97	1.42
2007	0.82	1.89	2.32	1.07	1.50
2008	0.98	2.08	2.44	1.10	1.47
2009	0.81	1.89	2.80	1.08	1.99
Capital productivity	*(Absolute Value)*				
2000	3.33	4.15	1.90	0.81	-1.43
2001	3.38	4.08	1.92	0.70	-1.46
2002	3.54	4.63	2.26	1.09	-1.28
2003	5.84	6.11	3.24	0.26	-2.60
2004	3.82	4.97	2.82	1.15	-1.00
2005	4.36	5.13	3.33	0.77	-1.03
2006	4.11	5.34	3.34	1.24	-0.77
2007	4.56	5.38	3.63	0.82	-0.93
2008	4.93	5.19	3.55	0.26	-1.38
2009	3.65	4.65	2.93	0.99	-0.72

Capital Intensity	*(Rs. in million)*				
2000	0.17	0.29	0.62	0.12	0.45
2001	0.15	0.26	0.57	0.11	0.42
2002	0.19	0.28	0.62	0.10	0.43
2003	0.16	0.31	0.61	0.15	0.45
2004	0.16	0.31	0.66	0.15	0.50
2005	0.17	0.30	0.60	0.14	0.43
2006	0.17	0.31	0.64	0.14	0.47
2007	0.18	0.35	0.64	0.17	0.46
2008	0.20	0.40	0.69	0.20	0.49
2009	0.22	0.41	0.96	0.18	0.73
Wage per employees	*(Rs. in thousands)*				
2000	19.89	40.12	60.57	20.23	40.68
2001	20.13	41.62	64.14	21.48	44.01
2002	23.07	41.82	63.88	18.75	40.80
2003	24.62	42.09	64.75	17.47	40.12
2004	22.38	41.80	67.60	19.42	45.22
2005	22.60	40.74	65.76	18.14	43.16
2006	19.27	34.05	56.67	14.78	37.39
2007	21.77	43.63	68.00	21.86	46.23
2008	26.55	46.56	73.08	20.02	46.53
2009	22.75	47.04	85.20	24.29	62.45

Note: *Refers to the gap in productivity and wage between the Tea, F&B, and Manufacturing industry.
Source: Own estimates.

3.5 GI and Indian Tea

3.5.1 Size and Growth of GI and NGI Firms: 2000-2009

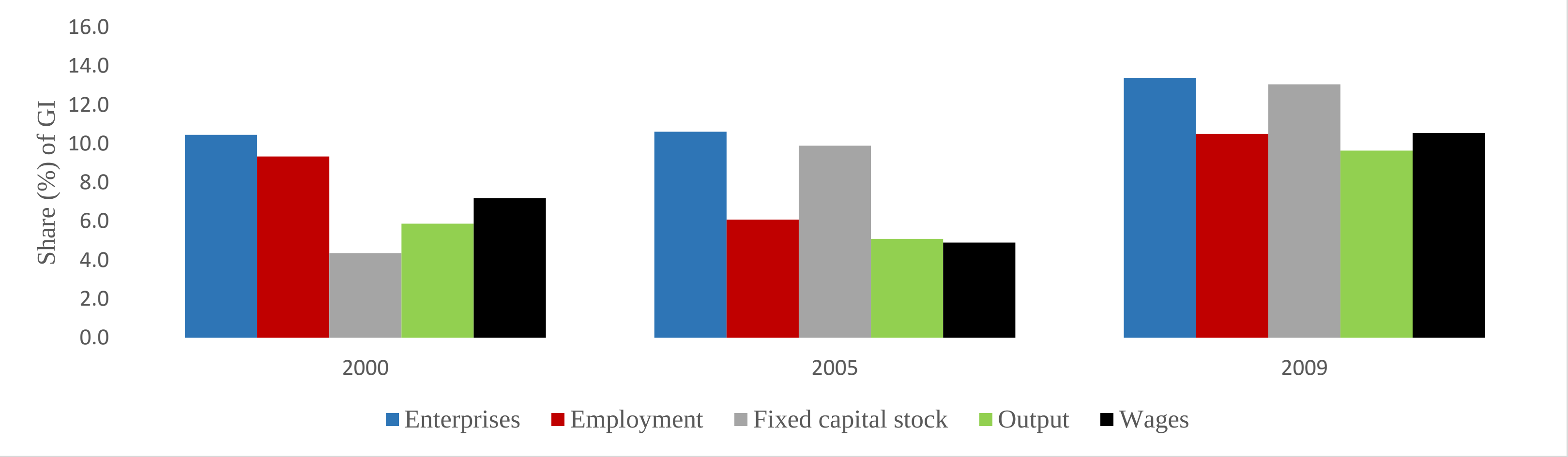
This section examines the performance of GI tea firms within the Indian tea industry from 2000 to 2009, using key indicators such as the number of firms, employment, fixed capital stock, output, and wages. Tea firms in Darjeeling, West Bengal, and Kangra, Himachal Pradesh, are categorized as GI tea firms based on their GI registration in 2005, while all other tea manufacturing firms in districts other than Darjeeling and Kangra are classified as NGI.

About 13 percent of tea firms are GI, marking a 3 percent increase between 2000 and 2009. Although the number of workers in GI firms declined from 11,720 in 2000 to 11,140 in 2009, the GI workforce's share in the tea industry rose from 9.3 percent to

10.5 percent (Figure 3.13), due to the overall decline in tea industry employment (Table 3.4). The share of GI firms in fixed capital stock rose significantly from 4.4 percent in 2000 to 13.1 percent in 2009, alongside increases in GI output and wages by 3.7 percent and 3.3 percent, respectively (Figure 3.13).

The growing presence of GI firms from 2000 to 2009 is primarily due to their faster growth compared to NGI firms (Table 3.4). GI firms grew at 0.3 percent per annum, while NGI firms declined at 2.8 percent per annum. Although employment declined in both GI and NGI firms, the decline was significantly higher in NGI firms. GI firms saw a higher rate of growth in fixed capital stock at 5.7 percent per annum compared to NGI firms. Similarly, output grew faster in GI firms at 8 percent per annum versus 2 percent for NGI firms. Wages declined in NGI firms but increased by 4 percent per annum in GI firms. The growing incidence of GI in the tea industry is attributed to the faster growth of GI firms and the decline of NGI firms.

Figure 3.13: Share (%) of GI Firms in Indian Tea industry (2000-2009)



Source: Own estimates.

Table 3.4: Size and Structure of Indian Tea industry (2000 to 2009)

	No. of Enterprises				Employment (in Thousands)				Fixed capital stock (Rs. in Millions)				Output (Rs. in Millions)				Wages (Rs. in Millions)			
	2000	**2005**	**2009**	**Growth**	**2000**	**2005**	**2009**	**Growth**	**2000**	**2005**	**2009**	**Growth**	**2000**	**2005**	**2009**	**Growth**	**2000**	**2005**	**2009**	**Growth**
GI	129	127	132	0.3	11.72	6.85	11.14	-0.6	919.45	1861.89	3073.36	5.7	4136.42	4185.90	8289.76	8.0	179.18	124.79	254.21	4.0
NGI	1104	1070	854	-2.8	113.68	105.75	94.80	-2.0	20176.79	16956.18	20455.52	2.1	66197.84	77875.06	77683.95	1.8	2315.06	2420.11	2155.89	-0.8
Total	1233	1197	986	-2.5	125.40	112.59	105.93	-1.9	21096.24	18818.07	23528.88	2.5	70334.27	82060.96	85973.70	2.3	2494.24	2544.90	2410.10	-0.4

Source: Own estimates.

3.5.2 Productivity and Wages: GI and NGI

Table 3.5 reveals trends in labour productivity and wages, showing that GI firms are less productive, and GI workers earn lower wages compared to NGI firms. In 2009, enterprise productivity, labour productivity and capital productivity of GI firms were about 1.5 times lower than those of NGI firms. However, GI firms were around 0.75 times more capital-intensive than NGI firms in 2009. Importantly, the wage gap has narrowed, with no significant disparity observed in 2009. Interestingly, while the gap in enterprise productivity and capital productivity widened from 2000 to 2009, the gap in labour productivity, capital intensity and wage per employee narrowed. This suggests an improvement in labour productivity along with capital intensity and wage payment of GI firms compared to NGI firms during the period.

Table 3.5: Productivity and Wage Difference: GI vs NGI Firms (2000-2009)

Year	GI	NGI	Total	Productivity gap*
Enterprise Productivity	*(Rs. in million)*			
2000	32.07	59.96	57.04	27.90
2001	28.40	46.90	45.03	18.51
2002	42.34	70.91	67.56	28.58
2003	37.75	93.11	86.98	55.36
2004	41.93	60.13	58.28	18.20
2005	32.96	72.78	68.56	39.82
2006	40.39	78.48	73.74	38.09
2007	52.17	93.52	87.70	41.35
2008	41.68	112.80	103.24	71.12
2009	62.80	90.96	87.19	28.16
Labour productivity	*(Rs. in million)*			
2000	0.35	0.58	0.56	0.23
2001	0.48	0.50	0.50	0.02
2002	0.60	0.67	0.66	0.06
2003	0.71	0.95	0.93	0.23
2004	0.58	0.62	0.61	0.03
2005	0.61	0.74	0.73	0.13
2006	0.58	0.71	0.70	0.13
2007	0.73	0.83	0.82	0.11
2008	0.71	1.00	0.98	0.29
2009	0.74	0.82	0.81	0.08

Capital productivity	*(Absolute Value)*			
2000	4.50	3.28	3.33	-1.22
2001	3.60	3.36	3.38	-0.23
2002	3.48	3.55	3.54	0.07
2003	4.18	5.96	5.84	1.78
2004	3.20	3.88	3.82	0.68
2005	2.25	4.59	4.36	2.34
2006	2.75	4.26	4.11	1.50
2007	4.05	4.61	4.56	0.56
2008	4.49	4.96	4.93	0.46
2009	2.70	3.80	3.65	1.10
Capital Intensity	*(Rs. in million)*			
2000	0.08	0.18	0.17	0.10
2001	0.13	0.15	0.15	0.02
2002	0.17	0.19	0.19	0.01
2003	0.17	0.16	0.16	-0.01
2004	0.18	0.16	0.16	-0.02
2005	0.27	0.16	0.17	-0.11
2006	0.21	0.17	0.17	-0.04
2007	0.18	0.18	0.18	0.00
2008	0.16	0.20	0.20	0.04
2009	0.28	0.22	0.22	-0.06
Wage per employees	*(Rs. in thousands)*			
2000	15.29	20.36	19.89	5.08
2001	19.69	20.16	20.13	0.48
2002	21.79	23.19	23.07	1.39
2003	20.62	24.89	24.62	4.27
2004	20.77	22.51	22.38	1.75
2005	18.23	22.89	22.60	4.66
2006	18.58	19.33	19.27	0.75
2007	22.39	21.70	21.77	-0.69
2008	20.73	27.02	26.55	6.29
2009	22.83	22.74	22.75	-0.08

Note: *Refers to the gap in productivity and wage between the GI and NGI firms.
Source: Own estimates.

3.6 Conclusion

In this chapter, we analyse the size, structure, and growth of the tea industry, assessing its overall development, productivity, and returns to workers. We observe a decline in the incidence of the tea industry over time, attributed primarily to the faster growth of F&B and manufacturing. We examine the magnitude of the tea industry across various firm-specific characteristics such as location, ownership, and age of the firm, focusing on five key indicators, namely, number of enterprises, employment, fixed capital stock, output, and wages. Our findings reveal that the F&B and manufacturing sectors outperformed the tea industry in all five parameters. The underperformance of the tea industry is primarily attributable to the faster growth of the F&B and manufacturing sectors. Significant variations in the prevalence of the tea industry across the firm characteristics show a higher presence in rural firms, privately owned firms, and older firms.

The growing share of GI firms in the tea industry is evident across all five indicators. This growth is partly due to the declining growth of NGI firms, alongside the positive and higher growth registered by GI firms. The narrowing capital intensity and wage gap among GI firms highlight the economic value of GI legislation. The findings suggest that GI legislation can help attract investment and improve workers' earnings.

Our results show that despite its importance, the tea industry is losing its share in Indian F&B and manufacturing. However, the positive gains reported by GI firms support the argument that GI legislation may help the industry become stronger and more competitive over time. To further understand the implications of these gains and the role played by GI, we conduct a comprehensive analysis in the following chapter.

CHAPTER 4

GI AND FIRM PERFORMANCE

4.1 Introduction

In Chapter 3, we looked at how the Indian tea industry has developed over time, focusing on production, fixed capital stock, employment, and wages. A comparative analysis from 2001 to 2009 revealed the poor performance of the tea sector relative to the Food & Beverages (F&B) and Manufacturing sectors. Markedly, significant growth disparities emerged between GI firms and non-GI (NGI) firms. We are interested to know if GI adoption played any role in this. This chapter aims to probe the effects of GI on tea firms, realizing the potential impact of Geographical Indications on firm performance.

Existing studies suggest that GIs boost firm performance through enhanced reputation, market competitiveness, innovation, and socio-economic contributions (Bramley et al., 2009; Matthews, 2009; Pike, 2015; Moreland, 2019). However, there have been instances where GIs yielded negative outcomes. For example, Bowen and Zapata (2009) argue that the tequila industry's mismanagement post-GI led to negative annual income for farmers and the local economy. Similarly, De Rosa et al. (2023) observes a reduction in the number of operators adhering to GI in the dairy sector in Southern Italy, highlighting negative dynamics associated with GI systems. Given the varied impact of GI across products and regions, its effects remain inconclusive. Thus, this chapter examines the impact of GI in the Indian tea industry, especially focusing on employment, fixed capital stock, output, and wages in tea manufacturing firms. Our objective is to provide empirical evidence on how GI influences these aspects.

The chapter is organised as follows: Section 4.2 provides details on the data used and the methodology employed, while the empirical results are discussed in Section 4.3. Section 4.4 concludes.

4.2 Data, Variables, and Methods

4.2.1 Data

This chapter is based on repeated cross-sectional data from the Annual Survey of Industries (ASI) of the Central Statistics Organisation, Government of India. The ASI provides comprehensive annual census-cum-survey data on formal manufacturing firms covering the whole of India. For our study, we extracted data on firms involved in the processing and blending of tea, focusing on the period from 1999-2000 to 2008-2009. This period was chosen because district-level identifiers, essential for distinguishing between GI and NGI firms, are not available post-2009. Tea firms located in the Darjeeling district (West Bengal) and the Kangra district (Himachal Pradesh), which received GI certification in 2005, are categorized as GI firms. All other tea manufacturing firms in districts other than Darjeeling and Kangra are classified as NGI firms.

The ASI provides detailed information on various variables such as location, output, employment, value-added, fixed capital stock, and wages and salaries. These variables were extracted for our study. We discuss the data in detail in the Chapter on Data and Methods. In addition to firm-specific controls, we incorporated district and state-level socio-economic variables to isolate the true effect of GI on firm performance. Our conjecture is that firms in more developed districts and states benefit from better socio-economic infrastructure, skilled labour, and human capital, which could enhance their performance. To control for these factors, we included district-level variables such as the number of bank branches, the share of Scheduled Tribe and Scheduled Caste population (an indicator of social backwardness), and literacy rate. At the state level, we used the poverty rate and the share of the urban population. The construction of these variables is presented in Table 4.1. Additionally, year effects were incorporated into the model to account for macro-level shocks that could impact firm productivity.

4.2.2 Construction of Variables

This subsection explains how we capture firm performance and construct our measure of GI adoption. We present the variables used in the analysis and their sources in Table 4.1.

Table 4.1: Construction of variables

Variables	Definition	Source
Dependent variables		
Employment	Total number of persons employed, including proprietors, owners and managerial staff.	ASI (Ministry of Statistics and Programme Implementation).
Output	Total ex-factory value of products and by-products manufactured as well as other receipts such as receipts from manufacturing and non-industrial services rendered to others.	ASI (Ministry of Statistics and Programme Implementation).
Fixed capital stock	Fixed capital stock consists of land, buildings and other constructions, plant and machinery, transport equipment, tools, and other fixed assets that have a normal economic life of more than one year from the date of acquisition.	ASI (Ministry of Statistics and Programme Implementation).
Wages per employee	Ratio of wages to employment. Wages include all regular monetary remuneration, such as direct wages, salaries, allowances, leave payments, and bonuses, but exclude lay-off payments (unless paid by the employer), social security contributions, and reimbursed business expenses.	ASI (Ministry of Statistics and Programme Implementation).

Independent variables		
Firm characteristics		
Age	Three binary variables for Young (aged less than 75 years), Middle-aged (aged between 75-150 years), and Old (aged above 150 years), respectively.	ASI (Ministry of Statistics and Programme Implementation).
Size	Three binary variables for Small (employing 10-99 employees), Medium (employing 100-199 employees), and Large (employing more than 200 employees) firms.	ASI (Ministry of Statistics and Programme Implementation).
Location	Binary variable for urban firms (urban = 1 and rural = 0).	ASI (Ministry of Statistics and Programme Implementation).
District-level controls		
Bank branch density	Bank branches per 100000 people.	Reserve Bank of India.
Share of ST population	Proportion of ST population in total population in a district.	Census of India.
Share of SC population	Proportion of SC population in total population in a district.	Census of India.
State-level controls		
Poverty rate	Poverty rate measured as the level of poverty (%).	Reserve Bank of India.
Share of urban population	Proportion of urban population in total population at the state level.	Census of India.

Source: Own construction.

Dependent Variables

We use four variables to capture firm performance: employment, gross output, fixed capital stock, and wages. These measures are widely recognised in the literature (Knack and Keefer, 1995; Niefert, 2005; Jorgenson et al., 2016; Kline et al., 2019; Bhattacharya et al., 2022). Employment is measured by the total number of persons engaged, including proprietors, owners, and managerial staff. Gross output includes the ex-factory value of products and by-products, along with receipts from manufacturing and non-industrial services. Fixed capital stock covers investment in land, buildings, machinery, transport equipment, and other assets with an economic life of over one year. Wages encompass all regular monetary remuneration, such as direct wages, salaries, allowances, leave payments, and bonuses, but exclude lay-off payments (unless paid by the employer), social security contributions, and reimbursed business expenses. Wages are reported in gross value, before deductions. Wages per employee are used in our estimations. To ensure comparability over time, output is deflated using the WPI for manufactured products (2004-05 prices), fixed capital stock using the WPI for machinery and machine tools (2004-05 prices), and wages using the CPI for industrial workers (2004-05 prices).

Independent Variables:

Our core independent variable is GI adoption, constructed as a binary variable that takes the value 1 for GI firms and 0 for NGI firms. Tea firms located in the Darjeeling district (West Bengal) and the Kangra district (Himachal Pradesh), which received GI certification in 2005, are categorised as GI firms. All other tea manufacturing firms in districts other than Darjeeling and Kangra are classified as NGI firms.

Control Variables

We include several firm-specific and state-specific control variables. Firm specific controls include the size of the firms (*size*), age of the firm (*age*), and location of the firm (*location*). *Location* is a binary variable indicating if a firm is in an urban area. Firm size is categorized into small (10-99 employees), medium (100-199 employees), and large (200+ employees), with small firms as the benchmark category. Firm age is categorized into young, middle-aged, and old, with young firms as the reference category. State-level controls include the share of Scheduled Tribe (ST share) and Scheduled Caste (SC share) populations, bank branches per 100000 people (bank branch density), share of people below the poverty line (poverty rate), and share of urban population in the total population (urbanization).

4.2.3 Method

To assess the impact of GI adoption on firm performance, we employ the Propensity Score Matching-Difference-In-Difference (PSM-DID) method, widely used to capture treatment effects or policy interventions (Lechner, 2011). This method allows us to address potential selection bias more effectively than, mere regression analysis.

PSM-DID involves matching a treated group with a non-treated group during the pre-treatment period, constructing a statistically comparable group based on observable characteristics (Khandker et al., 2010). By comparing the treated group with this ‘observationally similar’ non-treated group (control group), we can detect the effect of the treatment, avoiding the risk of comparing groups with dissimilar characteristics. Combining PSM with DID allows us to account for potential sources of selection bias by matching units in common support (Khandker et al., 2010).

The DID method compares treatment and comparison groups in terms of changes in outcomes over time relative to a pre-intervention baseline. In a standard 2x2 DID model, denoting Y_t^T and Y_t^C as outcomes for treated and control groups at time t respectively, the DID estimates the average treatment effect as:

$$DD = E(Y_1^T - Y_0^T | T_1 = 1) - E(Y_1^C - Y_0^C | T_1 = 0) \quad (1)$$

Where, $T_1 = 1$ signifies the post-treatment period, and $T_1 = 0$ denotes the pre-treatment period. DID allows for unobserved heterogeneity assuming that it is time-invariant, thereby cancelling out through differencing. This method is well-suited for estimating policy effects (Angrist and Krueger, 1998), and enables us to avoid selection bias associated with GI treatment[16] by comparing changes in outcome variables between pre- and post-GI treatment periods. The crucial assumption is the parallel trend path, where GI and NGI firms would follow similar paths over time without the treatment. Even if the assumption does not hold, matching with DID provides improved inference in DID models (Ryan et. al., 2018). This methodological approach ensures a robust analysis of the impact of GI adoption on firm performance, enhancing the credibility and reliability of our findings.

Given the availability of data for both pre- and post-enactment periods of the GI Act for both GI and NGI firms, we employ the DID method, expressed in the following form:

$$Y_{it} = \beta_0 + \beta_1 GI_i + \beta_2 POST_i + \beta_3 GI_i * POST_i + \varphi_j x_j + \omega_{it} \qquad (2)$$

where Y_{it} represents the outcome variable of firm performance for individual firm *i* at time *t*. Our dependent variables include employment, output, fixed capital stock, and wages. The binary variable GI takes the value 1 for GI firms (treated) and 0 for NGI firms (control). If β_1 is greater than zero and statistically significant, we conclude that the average performance of GI firms is higher than that of NGI firms. *POST* is a dummy variable indicating firm performance during the post-GI period (1 = post-intervention performance). If β_2 is greater than zero and statistically significant, it implies that the average performance of firms is significantly higher in the post-GI period compared to the pre-GI period. To capture the impact of GI intervention on firm performance, we introduce an interaction term *GI*POST*. Accordingly, β_3 is our coefficient of interest that estimates the effect of GI on outcomes. A positive and statistically significant β_3 would imply that GI protection has enhanced the

[16]GI application and registration is a non-random process, meaning firms may voluntarily choose to apply or not. Additionally, some firms may be denied registration even after applying.

performance of GI firms compared to NGI firms. To ensure that our interaction term captures the true effect of GI, we incorporate firm-level controls along with district and state-level controls. The vector X_j represents control variables including firm size, age, location, ST fraction, SC fraction, banking density, poverty rate, and share of urban population (Table 4.1), representing various socioeconomic factors likely to influence firm performance as documented in the literature. We also perform robustness checks to validate our main estimation using unmatched firms and firms only from West Bengal and Assam as sub-samples.

Initially, for the period 2000-2009, we had 5,557 observations. Our empirical investigation led us to apply the PSM technique to generate a matched comparison group using observable firm characteristics such as size, age, and location. This process resulted in 5,418 matched observations, comprising 462 treated and 4,956 control observations. Consequently, 139 observations were identified as unmatched. Figure 4.1 shows the matching of the estimated propensity scores of treated and untreated (control) groups based on measured baseline covariates[17].

4.3. Results

4.3.1 Characteristics of GI vs. NGI Firms

We begin by analyzing the characteristics of GI and non-GI (NGI) firms. Table 4.2 presents the mean differences (or tests of equality) between GI tea firms and NGI tea firms across various firm and regional characteristics. We conduct this comparison using a mean difference t-test for both the pre-GI (2000-2004) and post-GI (2005-2009) periods.

[17] For details, please refer Rosenbaum and Rubin (1983, 1984) and Austin (2009).

As expected, the majority of firms are NGI, with only around 9% classified as GI firms. In terms of size, small firms constitute a major share among GI firms compared to their share among NGI firms in both pre- and post-GI periods. Over 60% of GI firms are small, whereas their share in NGI firms is 23% in the pre-GI period and about 33% in the post-GI period. This difference is statistically significant at the 1% level in both periods. Medium-sized firms occupy a larger share among NGI firms in both periods, but the difference is statistically significant only in the post-GI period. In the post-GI period, medium-sized firms constituted about 50% of NGI firms compared to 30% of GI firms. A significant difference at the 1% level exists between GI and NGI firms in the large size category for both periods. More than a quarter of firms are large among GI firms in both periods, while their share among NGI firms was as low as 5%.

Unlike young firms, there is a significant difference between GI and NGI categories for middle-aged and old firms in both periods. The share of middle-aged firms is larger among NGI firms compared to GI firms. For instance, in the post-GI period, 51% of NGI firms were middle-aged compared to 42% of GI firms. In contrast, although the share of old firms is low in both GI and NGI categories, it is higher among GI firms compared to NGI firms.

Urban firms constitute a larger share among GI firms than NGI firms. However, the difference is statistically significant only in the pre-GI period, where about 7% of firms in GI districts and about 12% of firms in NGI districts are located in urban areas. There is a significant difference in the distribution of ST and SC populations between GI and NGI districts in both periods. The average share of the ST population in GI districts is about 12% and 17% in the pre- and post-GI periods, respectively, while in NGI districts, it is about 9% and 10%, respectively. Similarly, the average share of the SC population is about 17% and 12% in GI and NGI districts, respectively, in both periods.

GI districts appear to be financially more developed than NGI districts, with almost 75% of the population having bank branch coverage in the pre-GI period. This trend further improved to about 80% in the post-GI period. The banking density difference between GI and NGI districts is significant at the 1% level. Significant differences are also observed between GI states and NGI states in indicators such as the poverty rate and urbanization. The incidence of poverty in GI states is about 40% compared to 35% in NGI states in the pre-GI period. In the post-GI period, the incidence of poverty is higher in NGI states than in GI states: 30% in GI states versus 34% in NGI states. There is also a significant difference in urbanization in favor of GI states in both periods. The share of the urban population is about 28% and 19% in GI and NGI states, respectively, in both periods.

Table 4.2: Sample means

Variables	Pre-GI (2000-2004)			Post-GI (2005-2009)		
	GI	NGI	Mean difference test-t statistic	GI	NGI	Mean difference test-t statistic
Firm Size						
Small	0.6207 (0.4873)	0.3388 (0.4734)	-6.1519***	0.6371 (0.4827)	0.2406 (0.4275)	-9.7723***
Medium	0.3362 (0.4744)	0.3982 (0.4896)	1.313	0.3065 (0.4628)	0.4878 (0.5003)	3.8893***
Large	0.0431 (0.2039)	0.2631 (0.4404)	5.3311***	0.0565 (0.2317)	0.2716 (0.4449)	5.3174***
Age						
Young	0.5259 (0.5014)	0.5099 (0.5000)	-0.3304	0.4597 (0.5003)	0.4140 (0.4927)	-0.9863
Middle-aged	0.3362 (0.4744)	0.4661 (0.4990)	2.7039***	0.4194 (0.4954)	0.5100 (0.5000)	1.9327*
Old	0.1379 (0.3463)	0.0240 (0.1532)	-6.7252***	0.1210 (0.3274)	0.0760 (0.2651)	-1.769*
Location	0.1207 (0.3271)	0.0728 (0.2599)	-1.8651*	0.0806 (0.2733)	0.0627 (0.2425)	-0.7785
SC fraction	0.1645 (0.1133)	0.1183 (0.1105)	-4.5053***	0.1717 (0.0116)	0.1194 (0.1158)	-5.0238***
ST fraction	0.1257 (0.0326)	0.0939 (0.0830)	-4.0998***	0.1748 (0.0420)	0.1028 (0.0890)	-8.9200***
Bank branch density	0.7315 (0.1061)	0.5897 (0.1830)	-8.2275***	0.7975 (0.1117)	0.5687 (0.2116)	-11.8880***
Poverty	38.9793 (2.2022)	34.3536 (6.6229)	-7.4865***	29.3777 (4.1797)	33.8499 (4.8687)	9.8993***
Urban share	0.2715 (0.0443)	0.1908 (0.1051)	-8.2089***	0.2895 (0.0566)	0.1939 (0.1036)	-10.1292***
No. of observations	116	1414	1530	124	1355	1479

Note: Standard deviations in parentheses. ***p<0.01, **p<0.05, *p<0.10
Source: Own estimates.

4.3.2. Performance Analysis of GI and NGI Firms

We now shift our focus to understanding the differences in selected performance measures of GI and NGI firms during both the pre- and post-GI periods. This analysis is crucial before estimating the impact of GI on firm performance. Table 4.3 captures the performance differentials between GI and NGI firms during the pre- and post-intervention periods.

As the results show, the average employment, output, and fixed capital stock of NGI firms are higher than those of GI firms in both periods, with this difference being statistically significant at the 1% level. However, wages are significantly higher in GI firms compared to NGI firms, also at the 1% level, in both periods. Furthermore, while the output of both firm types increased in the post-GI period, the difference widened compared to the pre-GI period.

Unlike the employment trend in GI firms, employment in NGI firms has risen post-intervention. We also observe a rise in fixed capital stock for both firm types in the post-GI period compared to the pre-GI period. Regarding wages, a significant difference is observed between GI and NGI firms. Unlike NGI wages, GI wages increased after the intervention, and the difference has widened in the post-period relative to the pre-period. This wage difference is statistically significant at the 1% level. These trends are visually represented in Figures 4.1 to 4.4, which show a relatively upward-moving trend for GI firms, especially in fixed capital stock and wages, after the GI intervention.

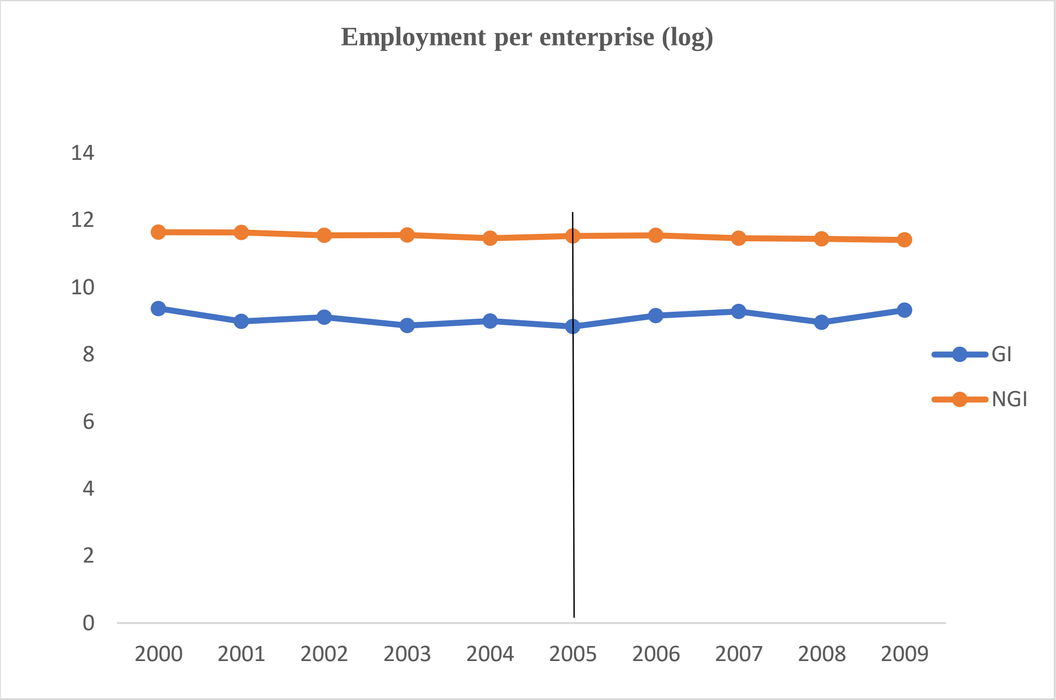
Considering the status of the performance indicators between the two periods, it is evident that GI firms have been able to attract higher investment in fixed capital stock and pay better wages than NGI firms. This provides a strong basis for investigating the impact of GI on the performance of GI and NGI firms.

Table 4.3: Measures of Performance of GI and NGI firms

Variables	Pre GI (2000-2004)			Post GI (2005-2009)		
	GI	NGI	t-test	GI	NGI	t-test
Employment (log)	4.3003 (0.5924)	4.7460 (0.7674)	6.1068	4.2593 (0.7180)	4.8819 (0.6969)	9.4972***
Output (log)	17.5084 (0.9123)	17.8794 (0.9286)	4.1414***	17.5287 (0.9113)	18.0103 (0.8428)	6.0475***
Fixed capital stock (log)	18.4673 (0.1389)	18.5355 (0.1813)	3.9515***	18.4897 (0.1392)	18.5502 (0.1753)	3.7390***
Wage (log)	9.9070 (0.3308)	9.8510 (0.3651)	-1.5982	9.9320 (0.2957)	9.7610 (0.3382)	-5.4430***
No. of observations	116	1414	1530	124	1355	1479

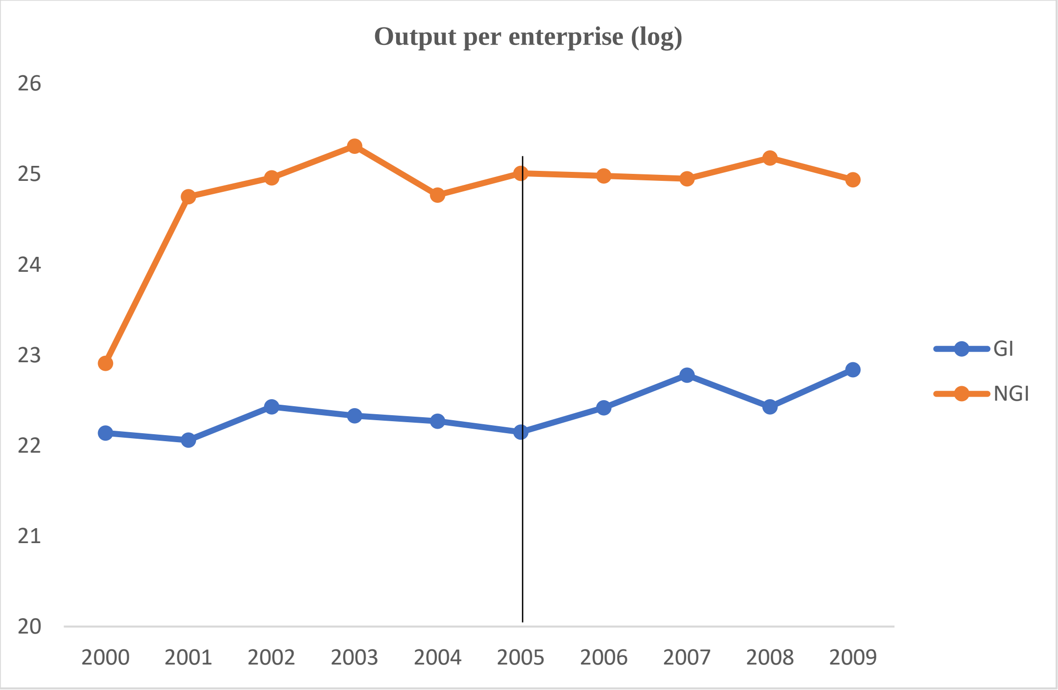
Note: Standard deviations are in parentheses. ***p<0.01, **p<0.05, *p<0.10
Source: Own estimates.

Figure 4.1: Trends in Employment, 2000-2009



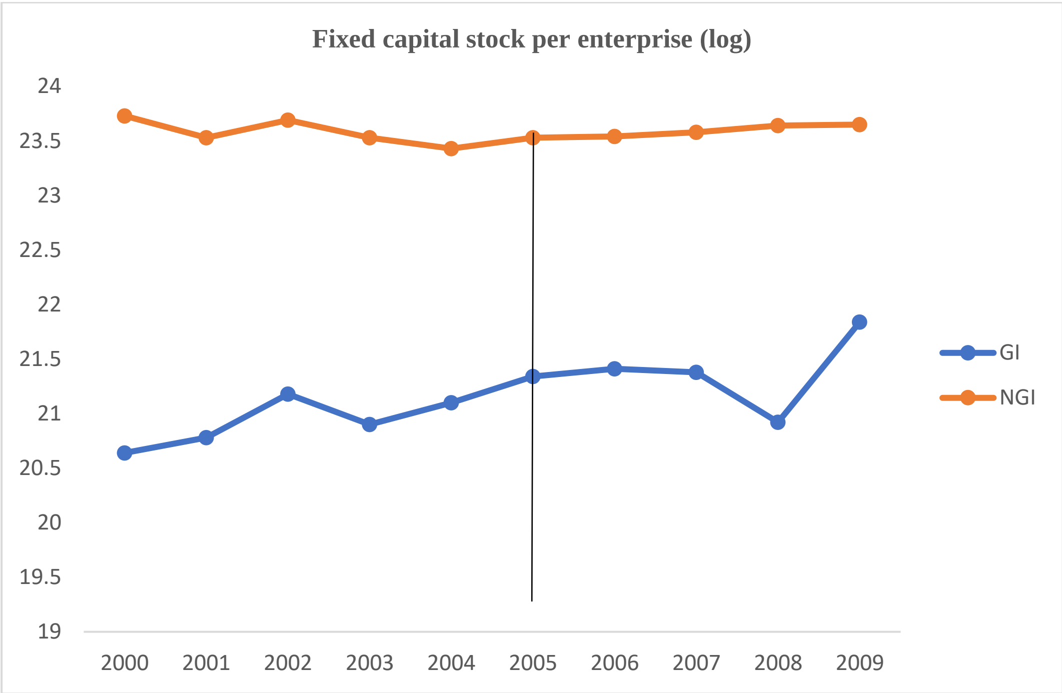
Source: Own estimates.

Figure 4.2: Trends in Output, 2000-2009



Source: Own estimates.

Figure 4.3: Trends in Fixed Capital Stock, 2000-2009



Source: Own estimates.

Figure 4.4: Trends in Wages, 2000-2009

Source: Own estimates.

4.3.3. Effects of GI on Firm Performance: DID Results

Table 4.4 presents the main findings of this chapter, highlighting the estimated impact of GI on firm performance. We employed the PSM-DID method to identify the GI effect, with the interaction term Treated*Post capturing this effect. This term represents the change in the treated group (GI firms) relative to the control group (NGI firms) during the post-treatment period.

Table 4.4: Impact of GI on Firm Performance: DiD Results

Independent Variables	Dependent Variable			
	Employment (log)	Output (log)	Fixed capital stock (log)	Wages (log)
	(1)	(2)	(3)	(4)
Treated	-0.0040 (0.0553)	-0.1971* (0.1141)	-0.0343*** (0.0124)	-0.2329*** (0.0509)
Post	0.1093** (0.0471)	0.1641* (0.0902)	0.0217 (0.0149)	0.0204 (0.0424)
Treated*Post	0.0112 (0.0740)	0.1597 (0.1320)	0.0321* (0.0172)	0.1318** (0.0553)
Size				
Medium	1.0269*** (0.0226)	0.9634*** (0.0411)	0.0878*** (0.0084)	-0.0005 (0.0200)
Large	1.6101*** (0.0243)	1.4440*** (0.0488)	0.2350*** (0.0114)	-0.0897*** (0.0186)
Age				
Middle-aged	0.1695*** (0.0220)	0.1952*** (0.0393)	0.0173** (0.0073)	-0.0260 (0.0168)
Old	0.1109** (0.0511)	0.0744 (0.0743)	0.0002 (0.0146)	-0.0135 (0.0291)
Location	-0.0565 (0.0615)	0.0846 (0.1079)	0.0017 (0.0120)	0.0661 (0.0598)
Bank Branch (log)	-0.5657*** (0.1484)	-0.2030 (0.3353)	-0.0255 (0.0617)	0.7339*** (0.1537)
SC fraction	-0.5822** (0.2460)	-0.7857 (0.5730)	0.0181 (0.0539)	-0.2008 (0.2869)
ST fraction	-0.2876* (0.1573)	-0.6483 (0.2910)	0.1099 (0.0454)	-0.1572 (0.1284)
Poverty rate	0.0009 (0.0024)	-0.0015 (0.0052)	0.0010 (0.0006)	0.0008 (0.0026)
Literacy rate	-0.0006 (0.0012)	-0.0013 (0.0026)	0.0000 (0.0003)	-0.0001 (0.0012)
Urban share	0.0376 (0.0709)	0.2529 (0.1699)	-0.0158 (0.0164)	0.2977*** (0.0823)
Year effects	Yes	Yes	Yes	Yes
Number of Observations	3009	3009	3009	3009
R-squared	0.7572	0.4302	0.3107	0.3203

Note: Standard errors are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: Own estimates.

The coefficient of interest is the interaction between the year and whether a firm is a GI or NGI firm, which we find statistically significant for some performance measures. Our results indicate that, on average, GI treatment increases firm investment in fixed capital stock and wages by about 3% and 13%, respectively. Specifically, the positive and significant coefficient for the interaction term related to fixed capital stock suggests a 3% increase in capital investment among treated firms relative to control firms during the period. This finding aligns with arguments suggesting that GI registration enables firms to attract investment (Marrano and Haskel, 2007; Corrado et al., 2009; van Heuvelen et al., 2021). Similarly, the significant coefficient for wages indicates that GI treatment positively influences wages by over 13% in GI firms compared to NGI firms. This aligns with the broader policy objective of ensuring better wages and welfare for workers in GI firms (WIPO, 2011; Ngokkuen and Grote, 2012; ILO, 2016; Rajbangshi and Nambiar, 2020).

Surprisingly, we found that employment and output were not significantly affected by GI treatment (Table 4.4). While acquiring GI rights is generally expected to grant some monopoly power, leading to increased output and employment, our results suggest otherwise. This is consistent with the findings in similar sectors, such as wine, where producers control yield to improve quality rather than increasing output (Giraud-Héraud et al.,2003; Réquillart, 2007). Consequently, this strategy may not lead to additional employment. Furthermore, the increasing use of capital, as suggested by our estimation, might substitute labour requirements or indicate a transitional phase where additional capital is needed to standardize production processes as mandated by GI registration. Additionally, the continued sale of counterfeit GI products by other players could affect the output and employment of

GI firms, highlighting the importance of proper implementation and regulation of GI laws.

Our estimation also shows that firm size and age positively impact output, which is expected. Banking density and urban share positively influence wages, while the negative impact of firm size on wages is unexpected, as larger firms typically pay more than smaller firms.

To sum up, our estimation demonstrates that GI positively impacts the performance of GI tea firms relative to NGI tea firms. To be precise, GI treatment successfully attracts additional investment in fixed capital stock and enhances wages paid by treated firms. Our findings contribute to the limited empirical literature on the impact of GI, which largely focuses on trade prospects and product prices in developed nations (Folkeson, 2005; Chever et al., 2012; Cei et al., 2017).

4.3.4 Robustness Check

To validate our main findings, we conducted robustness tests by examining the GI effect on sub-samples. To be specific, we conducted two separate analyses: (a) applied the same PSM-DID estimation to a sub-sample of firms exclusively from West Bengal and Assam[18], and (b) performed DID estimation on unmatched firms[19]. The results of these robustness tests, presented in Table 4.5, also show a positive effect of GI on fixed capital stock and wages. These additional analyses support our main findings, suggesting that GI registration consistently enables firms to improve their

[18] The rationale behind the selection of this sub-sample is that West Bengal and Assam are the largest contributors to the tea industry in terms of production, area of plantation, and employment (Tea Board of India, various issues).

[19] Unlike the matched sample, our unmatched sub-sample includes all tea manufacturing firms. This means we do not match the firms using PSM and simply perform DID on all firms.

performance relative to their counterparts. The consistency of these results across different sub-samples indicates that our main estimation is robust and reliable.

Table 4.5: Sample Split Analysis: DiD Results

Independent Variables	With firms located in West Bengal & Assam				With unmatched firms			
	Dependent Variables				Dependent Variables			
	Employment (log)	Output (log)	Fixed capital stock (log)	Wages (log)	Employment (log)	Output (log)	Fixed capital stock (log)	Wages (log)
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Treated	-0.2518**	-0.2527	-0.1527***	-0.5414***	0.0064	-0.2166*	-0.0343***	-0.2259***
	(0.1018)	(0.1754)	(0.0355)	(0.1022)	(0.0550)	(0.1170)	(0.0125)	(0.0498)
Post	0.0353	0.2659**	-0.0025	-0.1247***	0.1029**	0.1464	0.0206	0.0499
	(0.0575)	(0.1045)	(0.0219)	(0.0376)	(0.0485)	(0.0950)	(0.0146)	(0.0433)
Treated*Post	-0.0724	-0.0318	0.0430	0.1101*	0.0216	0.1949	0.0345**	0.1375**
	(0.1000)	(0.1452)	(0.0315)	(0.0663)	(0.0736)	(0.1357)	(0.0170)	(0.0549)
Size								
Medium	0.9711***	0.8734***	0.0825***	-0.0525***	1.0374***	0.9278***	0.0860***	-0.0134
	(0.0269)	(0.0458)	(0.0090)	(0.0202)	(0.0225)	(0.0465)	(0.0084)	(0.0210)
Large	1.5627***	1.3788***	0.2257***	-0.1296***	1.6168***	1.4167***	0.2337***	-0.0973***
	(0.0283)	(0.0534)	(0.0125)	(0.0192)	(0.0242)	(0.0513)	(0.0114)	(0.0188)
Age								
Middle-aged	0.1566***	0.1627***	0.0265***	0.0082	0.1753***	0.2152***	0.0176**	-0.0279
	(0.0229)	(0.0401)	(0.0082)	(0.0166)	(0.0221)	(0.0419)	(0.0072)	(0.0171)
Old	0.0887*	0.0084	0.0002	0.0069	0.1124**	0.1459	0.0035	-0.0152
	(0.0507)	(0.0751)	(0.0150)	(0.0293)	(0.0511)	(0.0984)	(0.0145)	(0.0291)

Location	-0.1631	-0.1401	0.0067	-0.0217	-0.0512	0.1085	-0.0001	0.0772
	(0.0757)	(0.1470)	(0.0164)	(0.0757)	(0.0594)	(0.1122)	(0.0115)	(0.0587)
Bank Branch (log)	-0.6597***	0.3014	0.0539	-0.3530	-0.5145***	-0.4670	-0.0531	0.6535***
	(0.2307)	(0.6102)	(0.1086)	(0.4941)	(0.1438)	(0.3811)	(0.0582)	(0.1516)
SC fraction	-1.2600***	-0.7314	-0.3539***	-2.1461***	-0.4754**	-0.9388	0.0017	-0.1837
	(0.4341)	(0.7781)	(0.1117)	(0.4005)	(0.2302)	(0.6871)	(0.0507)	(0.2755)
ST fraction	-0.0792	0.7571	0.1342	0.7071**	-0.2771*	-1.1181***	0.0581	-0.3451**
	(0.2676)	(0.5239)	(0.0929)	(0.3000)	(0.1675)	(0.3632)	(0.0452)	(0.1390)
Poverty rate	-0.0058	-0.0071	0.0020	0.0036	0.0010	0.0005	0.0010	0.0014
	(0.0057)	(0.0083)	(0.0021)	(0.0039)	(0.0024)	(0.0060)	(0.0006)	(0.0027)
Literacy rate	0.0106***	-0.0038	-0.0001	0.0119***	-0.0008	-0.0009	0.0000	-0.0004
	(0.0029)	(0.0055)	(0.0010)	(0.0030)	(0.0012)	(0.0030)	(0.0003)	(0.0012)
Urban share	0.3900**	0.2285	0.1573***	0.8940***	0.0021	0.3398	-0.0064	0.3080***
	(0.1529)	(0.2872)	(0.0430)	(0.1490)	(0.0653)	(0.2067)	(0.0153)	(0.0785)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2457	2457	2457	2457	3044	3044	3044	3044
R-squared	0.7823	0.4949	0.3120	0.1983	0.7553	0.3875	0.3022	0.3150

Note: Standard errors are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: Own estimates.

4.4 Conclusion

In this chapter, we examined the importance of GI in explaining the performance of tea firms in India, using firm-level data from the ASI for the period 1999-2000 to 2008-2009. We assessed the impact of GI treatment on firm performance using the PSM-DID method. Our results demonstrate the crucial role of GI treatment. We found strong evidence that GI treatment significantly influences firm performance, allowing firms to increase investment in fixed capital stock and pay higher wages. On average, GI treatment positively affects firms' investment in fixed assets by 3% and wages by about 13%. These findings are robust, as similar results were obtained in our sub-sample analysis. Overall, our empirical analysis suggests the importance of GI registration in explaining the performance of tea firms in India.

In the next Chapter, we delve deeper into the wage differences between GI and NGI firms, along with probing the factors that explain these differences. In particular, Chapter 5 probes the impact of GI treatment on wages.

CHAPTER 5

GI AND WAGE IMPLICATIONS

5.1 Introduction

In Chapter 4, we explored the impact of GI on firm performance, which revealed a positive effect of GI on firms' investment and wages. These findings support the premise that GI protection is beneficial to firms. Discussions on GIs often emphasize their welfare aspects, enabling workers to enhance their livelihoods and alleviate poverty (Rangnekar, 2004; Ngokkuen and Grote, 2012; Ghosh, 2016). Granting such protection, besides fostering innovation, ensures that workers involved in the innovation are rewarded (WIPO, 2009). Therefore, the potential economic and welfare gains of GI protection, particularly for those employed in the tea industry, warrant further scrutiny (Poetschki et al., 2021; Zhang et al., 2023).

Better pay is associated with higher poverty alleviation, particularly in sectors such as plantations where the workforce often comes from economically disadvantaged backgrounds. However, the tea industry is well-known for its low wage rates relative to similar employment categories in India (Sarkar, 2016; Siegmann and Sathi, 2022). Moreover, existing literature highlights varying wage trends in India across regions, locations, sectors, and genders (Bhadra, 2004; Das, 2012; Duraisamy and Duraisamy, 2016; Das and Usami, 2017; Kumar and Pandey, 2021). Despite the contentious and politically charged nature of the wage issue, especially in the tea sector, studies examining its implications are scarce. Importantly, the impact of GI protection on wages has received minimal attention, limited to conceptual and theoretical advocacy suggesting its potential benefits for workers and rural economies (Bramley et al., 2009; WIPO, 2021).

In this chapter, we investigate the wage implications of GI adoption. We offer a comprehensive understanding of the GI effect, alongside other factors contributing to wage differences across tea firms. Our primary objective is to assess whether a wage gap exists between GI and non-GI (henceforth, NGI) tea firms and to identify the factors influencing this gap.

The chapter is divided into five sections. Section 5.2 presents the data and methods, including the construction of variables, descriptive statistics, and wage distribution. Section 5.3 discusses our empirical results, examining the sources of the GI wage gap across the wage distribution, using both Oaxaca and Recentered Influence Function (RIF) decomposition techniques. Finally, the conclusion is presented in Section 5.4.

5.2 Data and Method

5.2.1 Data and Variables

We conduct our analysis using the Annual Survey of Industries (ASI) data, focusing on formal manufacturing firms within the Indian tea sector. As the data used in this chapter is the same as in Chapter 4, we will not discuss it again. Detailed information about the data and its cleaning can be found in Section 4.2.1 of Chapter 4. Our final sample consists of 4,440 observations, with 4025 classified as Non-GI (NGI) firms and 415 as GI firms.[20]

[20] Following established practice in the literature, we dropped observations with discrepancies such as negative fixed capital, negative employment, and age of the firms equal to zero or abnormally high. Observations with missing values were also excluded. As detailed in Chapter 4, tea firms in the Darjeeling district (West Bengal) and Kangra district (Himachal Pradesh), which received GI certification in 2005, are categorised as GI firms, while others are classified as non-GI firms.

Construction of Variables

This section discusses the construction of variables for our analysis. As this chapter examines the role of GI in explaining wage gaps between GI and NGI firms, we first define the wage gap, and then explain the categorization of firm ownership based on GI status. Table 7.1 provides a summary description of the variables considered in our analysis.

Table 5.1: Construction of variables

Variables	Definition
Dependent variable	
Wages per employee (log)	Ratio of wages to employment. Wages include all regular monetary remuneration, such as direct wages, salaries, allowances, leave payments, and bonuses, but exclude lay-off payments (unless paid by the employer), social security contributions, and reimbursed business expenses.
Independent variables	
Firm characteristics	
Size	
Small	Binary variable for firms employing 10 to 99 employees
Medium	Binary variable for firms employing 100 to 199 employees
Large	Binary variable for firms employing 200 and above employees
Age	
Young	Binary variable for firms aged less than 75 years
Middle-age	Binary variable for firms aged between 75 to 150 years
Old	Binary variable for firms that have completed more than 150 years since inception
Capital intensity	Logarithm of the ratio of capital invested per person engaged
District effects	
Bank branch density	Bank branch density per 100000 people
Share of SC population	Proportion of SC population in total population in a district
Literacy rate	Percentage of population aged seven or above in a district who can read or write
State effects	
Urbanisation	Proportion of urban population in total population at the state level

Source: Own construction.

Dependent variable

Our dependent variable is the wage gap, measured as the difference in wages per employee between GI and NGI firms. Data on wages are drawn from ASI datasets, which include all regular monetary remuneration, such as direct wages, salaries, allowances, leave payments, and bonuses, but exclude lay-off payments (unless paid by the employer), social security contributions, and reimbursed business expenses. Wages are reported in gross value, before deductions. To ensure comparability over time, we deflate wages using the CPI for industrial workers (2004-05 prices). We calculate wages per employee by dividing real wages by the total number of persons engaged.

Independent variables

Our main independent variable is GI adoption, as explained in Chapter 4. In brief, GI firms are located in the Darjeeling district (West Bengal) and Kangra district (Himachal Pradesh), while NGI firms include all others. Other independent variables in our model represent various firm level and regional level characteristics. Firm level characteristics include size, age, and capital intensity. Firm size is categorized into small (10-99 employees), medium (100-199 employees), and large (200+ employees), with small firms as the benchmark category. Firm age is categorized into young, middle-aged, and old, with young firms as the reference category. Capital intensity is measured as the ratio of gross fixed assets to employment. Regional-level variables encompass bank branches per 100,000 people (bank branch density), the percentage of SC population in the total population (SC share), the percentage of people who can read or write at the district level (literacy rate), and the percentage of urban population to the total population (urbanisation).

Descriptive statistics

Table 5.2 presents the descriptive statistics. We observe that the majority of firms belong to the NGI category (almost 90 percent). On average, a worker is paid around Rs 20,000 per annum. An average firm in our dataset is medium-sized and middle-aged, with a capital intensity of around Rs 1,80,000. At the district level, the average literacy rate is around 60 percent, and the share of the SC population is approximately 13 percent. On average, there are six bank branches per 100000 people. At the state level, about 20 percent of the population resides in urban areas.

Table 5.2: Descriptive statistics

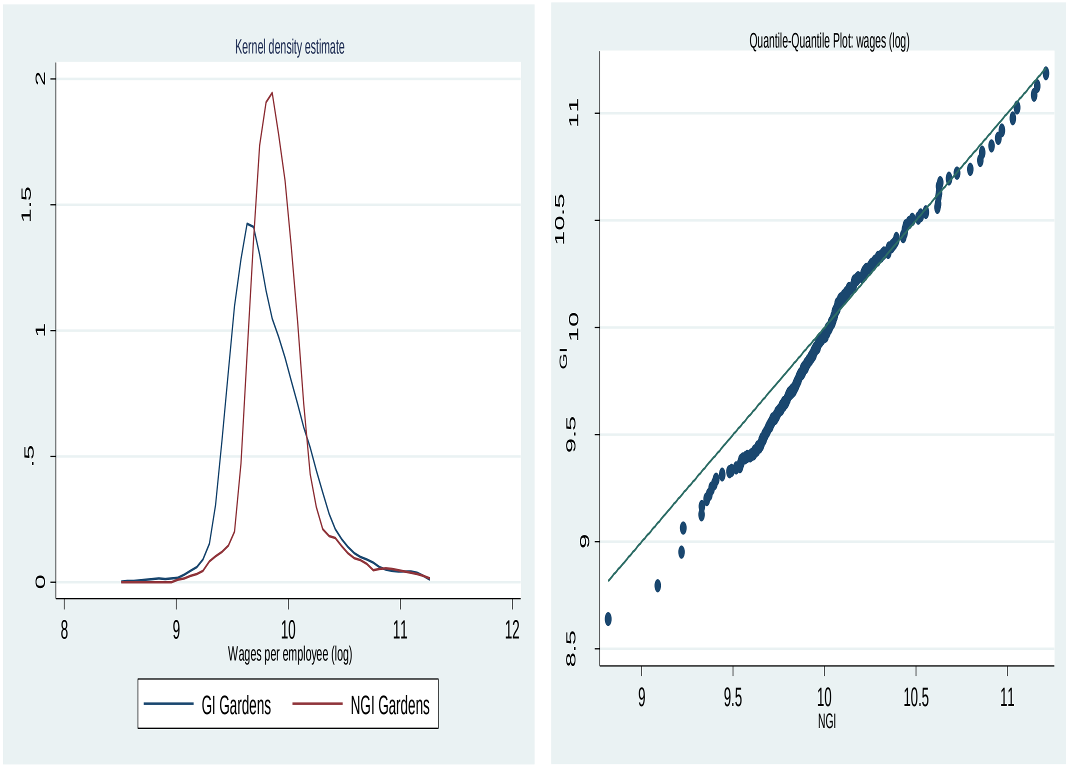
Variables	Obs.	Mean	Std. Dev	Min	Max
Dependent Variable					
Wages (log)	4,440	9.8804	0.4074	5.8927	11.2125
Independent Variables					
Size	4,440	1.4402	0.6514	1	3
Age	4,440	1.4800	0.6101	1	3
Capital intensity (log)	4,440	11.627	1.1240	3.8171	15.7041
Bank branch density	4,440	6.0466	2.0630	2.5651	23.1260
Literacy rate	4,440	0.6310	0.0791	0.2907	0.8695
Share of SC population	4,440	0.1260	0.1093	0.0027	0.5013
Urbanisation	4,440	0.2357	0.1198	0.0943	0.9676

Source: Own estimates.

Wage Distributions

To further examine the wage gap between GI and NGI firms, we use kernel density plots and quantile-quantile plots (Figure 5.1). Both plots provide substantial evidence of a wage gap. The larger portion of the NGI wage distribution is to the right of the GI firms, indicating a larger gap on the left-tail and middle of the distribution, with near overlap in the right-tail. The quantile-quantile plot also shows that NGI firms generally pay higher wages than GI firms (Figure 5.1). The distribution of the wage gap enables us to understand the variation of the GI effect at different deciles. At the bottom quantile, GI firms pay higher wages than NGI firms. However, in the middle and top quantiles, NGI firms pay more than GI firms. The wage gap distribution is graphically shown in Figure 5.2, indicating a consistently increasing wage gap from lower to higher quantiles. Specifically, the wage gap is larger in firms paying higher wages than those paying lower wages. This wage difference between GI and NGI firms is also evident in Table 5.3, which presents the logarithm of wages paid at different quantiles. Thus, Figure 5.2 shows a rising gap between GI and NGI firms along the wage distribution. However, whether this gap can be attributed to GI adoption requires further empirical investigation. The density plots (kernel and quantile-quantile plots) suggest the influence of GI on wages, but we delve deeper into this issue in the next section, where we employ econometric tools to establish the wage implications of GI adoption.

Figure 5.1: Wages by firm category



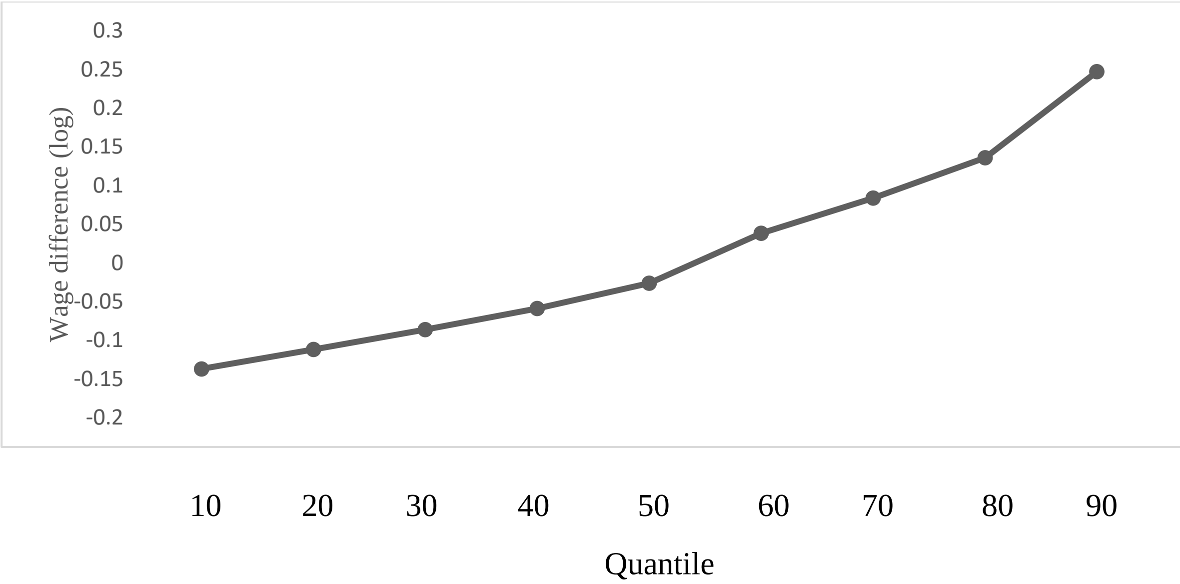
Source: Own estimates.

Table 5.3: Wage gap across deciles

Percentile	NGI	GI	Wage gap
(1)	(2)	(3)	(4) = (2 minus 3)
0.1	9.4819	9.6188	-0.1369
0.2	9.5865	9.6981	-0.1116
0.3	9.6704	9.7564	-0.086
0.4	9.7475	9.8065	-0.059
0.5	9.8325	9.8587	-0.0262
0.6	9.9448	9.9064	0.0384
0.7	10.0518	9.9676	0.0841
0.8	10.1817	10.0455	0.1362
0.9	10.3882	10.1408	0.2474

Note: The wage gap is the difference between the log wage of GI and the log wage of NGI.
Source: Own estimates.

Figure 5.2: GI-NGI wage gap at quantiles



Source: Own estimates.

5.2.2 Method

This chapter investigates the factors contributing to the wage gap between GI and Non-GI firms using Oaxaca and Recentered Influence Function (RIF) decomposition methods (Firpo et al., 2007, 2009, 2017; Jann, 2008; Rios-Avila, 2020). We begin by performing a decomposition at the mean, estimating a model of the determinants of (log) wages for GI and Non-GI firms as follows:

$$lnW_{Lig} = Z'_{eg}\alpha_g + E_{eg};\ e = 1, \ldots\ldots, n; g = gi, ngi \qquad (1)$$

where i denotes the firm; g represents the status of the firms, GI (gi) or Non-GI (ngi); lnW_{Lig} is the logarithm of wages; Z'_{eg} is the vector of firm-level characteristics likely to influence wages; and E_{eg} is the random error term. Equation (1) is estimated using ordinary least squares, assuming zero mean and constant variance.

$$D_W = \overline{lnW}_{Lngi} - \overline{lnW}_{Lgi} = (\overline{Z'}_{ngi}\hat{\alpha}_{ngi}) - (\overline{Z'}_{gi}\hat{\alpha}_{gi}) \qquad (2)$$

Here, D_W represents the difference in expected wage values between GI and Non-GI firms from equation (1).

Using the Oaxaca decomposition (2007), we then decompose the wage gap into components attributable to differences in observable characteristics (composition effect) and differences in returns to coefficients (structural effects):

$$D_W = (\overline{Z'}_{\mathrm{ngi}}\hat{\alpha}_{\mathrm{ngi}}) - (\overline{Z'}_{\mathrm{gi}}\hat{\alpha}_{\mathrm{gi}}) = (\overline{Z}_{\mathrm{ngi}} - \overline{Z}_{\mathrm{gi}})'\ \hat{\alpha}_{\mathrm{ngi}} + \overline{Z'}_{\mathrm{gi}}\,(\hat{\alpha}_{\mathrm{ngi}} - \hat{\alpha}_{\mathrm{gi}}) \qquad (3)$$

Where, $\hat{\alpha}_{\mathrm{g}}$ is the estimated value of α_{g}. The term $(\overline{Z}_{\mathrm{ngi}} - \overline{Z'}_{\mathrm{gi}})'\ \hat{\alpha}_{\mathrm{ngi}}$ in equation (3) is the explained part of the GI wage gap, capturing the gap explained by differences in observed characteristics (composition effect) at the mean, weighted by the coefficients attributable to NGI firms (α_{ngi}). NGI firms are used as the reference category for the decomposition. Similarly, $\overline{Z'}_{\mathrm{gi}}\ (\hat{\alpha}_{\mathrm{ngi}} - \hat{\alpha}_{\mathrm{gi}})$ represents the unexplained part, capturing wage differences not explained by observed predictors. This is termed the structural effect, likely denoting heterogeneous responses to covariates by GI status, omitted variables, model misspecification, and measurement error.

Following Gang et al. (2022), we perform the RIF decomposition at all deciles of the wage distribution. To implement this, we use the RIF approach developed by Firpo et al. (2009, 2018). This method quantifies the impact of each variable in explaining the wage gap at different quantiles of the wage distribution. Furthermore, the reweighting approach counters the inherently parametric nature of the basic Oaxaca decomposition (Firpo et al., 2009). The coefficients of categorical variables are normalized to prevent any omitted reference groups (Gang et al., 2022).

The procedure involves two stages. In the first stage, a counterfactual distribution is created through a reweighting procedure to decompose the wage gap between GI and NGI firms into composition and structural effects. The reweighting function is estimated using a logit regression. In the second stage, the RIF decomposition method estimates the contribution of each explanatory variable to both the composition and structural effects. The RIF decomposition is similar to the Oaxaca method, except the outcome variable is replaced with the RIF of the target statistics. We then conduct an Ordinary Least Squares (OLS) regression analysis of the corresponding RIF on observed characteristics for GI firms, NGI firms, and the counterfactual. These estimates decompose the difference in distributional parameters between GI and NGI firms by substituting the logarithm of wages with the respective RIF for each observation and using an appropriate counterfactual (Khurana and Mahajan, 2020). In addition to the detailed composition and structural effects derived; the aggregate composition and structural effects produced by the reweighting method are further divided into pure composition effects, specification error, and pure structural effects and reweighted error, respectively. We can also generate the contribution of each explanatory variable to pure composition effects, specification errors, pure structural effects, and reweighted errors. This allows us to estimate detailed structural and composition effects, providing insights into the factors driving the wage gap between GI and NGI firms.

5.3 Empirical Analysis and Discussion

5.3.1 Baseline Determinants of Wages of GI and NGI Firms

Table 5.4 shows the ordinary least squares estimates with wages as the dependent variable and GI status as the main independent variable. The pooled regression (column 1) captures an intercept shift, indicating that covariates have a uniform influence across both GI and non-GI firms, without interaction with the firm's GI status. To better understand the impact of GI status on wages, we conducted separate estimations for GI and non-GI firms. While we do not aim to infer causality due to potential endogeneity issues, our objective is to highlight the importance of these factors, especially the firm category (GI/NGI), in explaining wage differences.

Table 5.4: Determinants of log wages, ordinary least square estimates

Independent Variables	**Dependent Variable**		
	All Firms wages (log)	**GI Firms wages (log)**	**NGI Firms wages (log)**
GI	-0.1403*** (0.0167)	-	-
Size			
Medium	-0.0225* (0.0131)	-0.0513 (0.0450)	-0.0163 (0.0135)
Large	0.0894*** (0.0202)	0.0368 (0.0997)	-0.0845*** (0.0204)
Age			
Middle-aged	-0.0228* (0.0121)	-0.0033 (0.0997)	-0.0194 (0.0129)
Old	-0.0176 (0.0234)	-0.0155 (0.0492)	-0.0100 (0.0270)
Capital intensity (log)	0.0551*** (0.0048)	0.0067 (0.0159)	0.0626*** (0.0049)
Bank branch density (log)	0.0296 (0.0121)	-8.8668 (10.2273)	-0.0648** (0.0325)
Literacy Rate	0.0090*** (0.0011)	1.1391 (12.1961)	0.0095*** (0.0011)
Share of SC population	-0.0028*** (0.0008)	-1.3602 (27.2268)	-0.0055*** (0.0008)
Urbanisation	0.0116*** (0.0009)	-0.1566 (2.1741)	0.0152*** (0.0009)
Year effects	Yes	Yes	Yes
Constant	8.7061*** (0.3634)	-119.3480 (311.0600)	7.6327*** (0.3738)
No of Obs.	4440	415	4025

Note: The dependent variable is the logarithm of wages per employee. Standard errors reported in parentheses are robust to heteroskedasticity and clustered residuals within districts. Sampling weights are used in estimation.
***, **, and * denote significance at the 1,5, and 10 percent levels, respectively.
Source: Own estimates.

Across firm categories (GI/NGI), the effect of size and age on wages is similar. Wages decrease with an increase in size, meaning larger firms pay less. Interestingly, higher capital intensity has a positive effect on wages, especially for NGI firms and in pooled estimations. Similarly, the positive coefficient of bank branch density indicates that greater access to finance enables firms to grow and pay higher wages (Buera et al., 2012; Sahay et al., 2015). In line with the literature, the positive coefficient of literacy rate establishes that higher literacy and skill contribute to higher earnings (de Baldini Rocha and Ponczek, 2011; Green and Riddell, 2022). On the other hand, the negative coefficient of the share of the Scheduled Caste (SC) population suggests that firms in socially backward regions tend to pay less than firms in other regions. Improved urbanization, with a higher share of the urban population, generally provides greater access to economic opportunities for firms, enabling them to pay more to their workers. As Buchholz (2023) argues, workers receive higher wages in urbanized regions. Similarly, a positive coefficient of the urbanisation variable indicates that firms with locational advantages are likely to pay more than firms with locational disadvantages.

We observe a differential effect of factors on firm wages. Capital intensity, bank branch density, and urbanisation positively influence wages. On the other hand, factors like size, age, and SC share negatively influence wages. These findings suggest that different factors impact wages differently across firm categories. Overall, our results confirm the importance of capital intensity, banking access, and urbanization in determining higher wage levels in the Indian tea manufacturing industry.

5.3.2 *Oaxaca Mean Decomposition of the Sources of Wage Gaps*

The findings from Table 5.3 indicate a wage gap between GI and NGI firms. To identify the factors contributing to this gap, we employ the standard Oaxaca decomposition method. Additionally, we use RIF-Oaxaca decomposition at the mean and various quantiles. The results of the overall decomposition, Pre-GI decomposition, and Post-GI decomposition are presented in Table 5.5. The table divides the wage gap decomposition into overall effect, composition effect, and structural effect for each covariate. The overall wage gap between GI and NGI firms is around 3 percent. However, this gap diminishes from 4.5 percent in the Pre-GI period (2000-2004) to around 1.3 percent in the Post-GI period (2005-2009), indicating that GI intervention is mitigating the existing wage gap.

Table 5.5: Standard Oaxaca decomposition of wage gap

	Overall (2000-2009)			Pre (2000-2004)			Post (2005-2009)		
		Composition effect	**Structural effect**		**Composition effect**	**Structural effect**		**Composition effect**	**Structural effect**
Difference	0.0298* (0.0180)			0.0440** (0.0203)			0.0125 (0.0301)		
Aggregate effects		-0.1147*** (0.0076)	0.1445*** (0.0192)		-0.0768*** (0.0114)	0.1209*** (0.0208)		-0.1388*** (0.0107)	0.1513*** (0.0328)
Size		-0.0119*** (0.0029)	0.0031 (0.0438)		-0.0079** (0.0035)	0.0891** (0.0398)		-0.0160*** (0.0047)	-0.0805 (0.0764)
Age		0.0039 (0.0027)	-0.0661 (0.0431)		0.0073 (0.0054)	-0.0305 (0.0444)		0.0001 (0.0023)	0.0013 (0.0719)
Capital intensity (log)		-0.0048 (0.0033)	0.6887*** (0.2004)		0.0047 (0.0054)	0.0210 (0.1785)		-0.0113*** (0.0043)	1.3862*** (.3665)
Bank branch density		-0.0079 (0.0051)	0.2500 (0.4981)		0.0081 (0.0062)	1.0266 (2.1763)		-0.0068 (0.0083)	2.6767** (1.1635)
Literacy rate		-0.0221*** (0.0037)	0.8971 (3.9528)		-0.0291*** (0.0047)	0.4404 (10.1316)		-0.0177*** (0.0062)	-16.7670 (19.3775)
Share of SC population		0.0107*** (0.0022)	-3.2026 (5.0882)		0.0054** (0.0022)	-5.6410 (14.2303)		0.0233*** (0.0041)	4.3092 (23.2506)
Urbanisation		-0.0825*** (0.0068)	0.2962 (1.3958)		-0.0655*** (0.0089)	-0.2375 (3.2990)		-0.1103*** (0.0106)	2.6287 (6.2154)
Intercepts		NA	1.2780 (2.5492)			4.4527 (5.9716)		NA	5.9966 (11.1282)
No of Obs.		4440	4440		2325	2325		2115	2115

Note: The dependent variable is the logarithm of wages per employee. Robust Standard errors reported in parentheses are clustered at the district level. Sampling weights are used in estimation. ***, **, and * denote significance at the 1,5, and 10 percent levels, respectively.
Source: Own estimates.

We now discuss the results of the decomposition estimations. First, we consider the standard Oaxaca decomposition (Table 5.5). Then, we examine the RIF-Oaxaca decomposition results at the mean (Table 5.6) and selected deciles (Table 5.7). Our focus is on explaining the wage gap attributable to differences in observables and returns to these observables. The standard Oaxaca decomposition illustrates the wage gap decomposition into composition and structural effects, both overall and for each covariate. For better understanding, we interpret the results of composition and structural effects, noting that a positive coefficient widens the gap while a negative coefficient narrows it.

In Table 5.5, the composition effect is negative, indicating it narrows the wage gap, while the structural effect is positive, meaning it widens the gap. Both effects are significant at the 1 percent level. The composition effect, representing the difference in observable characteristics between GI and NGI firms, narrows the wage gap by about 12 percent, contributing to 44 percent of the wage gap. This implies that if GI firms had similar endowments and advantages as NGI firms, the wage gap would be reduced by 44 percent. However, the structural effect is more influential, widening the wage gap by about 15 percent, accounting for 56 percent of the wage gap. This suggests that if the variables determining wages yielded similar returns for GI and NGI firms, the wage gap would decrease by 56 percent. Essentially, the structural disadvantage of GI firms drives them to pay less than NGI firms.

A closer examination of the composition effect reveals that not all covariates significantly contribute to its size. The largest contributor to the composition effect is the difference in the rate of urbanisation between the locations of GI and NGI firms, accounting for over 8 percentage points of the wage gap. Another important factor is the difference in regional characteristics, namely, literacy rate and the share of the SC population, accounting for around 2 percent and 1 percent, respectively. Our findings align with the literature, indicating that backward social groups face lower employment shares and wage discrimination (Dutta 2004; Das and Dutta, 2007; Majumder, 2007; Agarwal, 2014; Abraham, 2017; Duraisamy and Duraisamy, 2017). Tea firms, typically located in underdeveloped regions, and predominantly employing rural communities from backward social groups, face similar discrimination (Thorat, 2007; Deshpande, 2011; Arya, 2015; Hazarika, 2012; Das, 2016). Other covariates, such as differences in size, also contribute to the composition effect, reducing the wage gap by around 1.2 percent.

Capital intensity is the only significant factor in explaining the wage gap between GI and NGI firms through structural effects, increasing the gap by about 70 percent. Other factors are not statistically significant in explaining the structural effects on the wage gap. Our results highlight the importance of firm and regional characteristics in explaining the wage gap. Their importance is evident from their respective contributions to composition and structural effects in explaining wage inequality.

5.3.3 RIF-Oaxaca Distributional Decomposition of the Sources of Wage Gaps

The results of the RIF decomposition are presented in the following two subsections. The first section shows the decomposition of the average wage gap, while the second subsection identifies the difference in the wage gap and its determinants at every decile of the wage distribution.

Decomposition of average wage gap

The RIF-Oaxaca results for differences in average wages are presented in Table 5.6. The first column shows the estimates of mean decomposition. The counterfactual represents our estimated wage distribution, indicating what the wages of GI firms would have been if they had similar coefficients as NGI firms. The pure components, pure composition effects, and pure structural effects denote the differences net of specification and reweighting errors. Concerns related to the standard Oaxaca decomposition, such as fulfilment of the linearity assumption, are crucial for consistent estimation of composition and structural effects (Firpo et al., 2018). Our results show a non-significant specification error, indicating that our model is correctly specified. In addition, the reweighting error is non-significant, suggesting that our reweighting factors are consistently estimated.

Table 5.6: RIF-Oaxaca Decomposition at mean

Overall	Estimate	
Mean NGI wage (N)	9.8844***	(0.0549)
Mean GI wage (G)	9.8546***	(0.0270)
GI gap in wage (N-G)	0.0298	(0.0612)
Reweighted decomposition		
Counterfactual (C)	10.0243***	(0.0526)
Total composition effect (N-C)	-0.1398**	(0.0459)
Total structural effect (C-G)	0.1697	(0.0601)
RIF aggregate decomposition		
Pure composition effect	-0.1385***	(0.0263)
Specification error	-0.0014	(0.0384)
Pure structural effect	0.1466***	(0.0373)
Reweighting error	0.0230	(0.0530)
Pure composition effect		
Size	-0.0121	(0.0110)
Age	0.0032	(0.0060)
Capital intensity (log)	-0.0068*	(0.0035)
Bank branch density	-0.0102	(0.0356)
Literacy Rate	-0.0261	(0.0266)
Share of SC population	0.0116	(0.0135)
Urbanisation	-0.0981**	(0.0427)
Pure structural effect		
Size	-0.0063	(0.0187)
Age	-0.0494***	(0.0175)
Capital intensity (log)	0.5396	(0.4273)
Bank branch density	0.2865	(0.4025)
Literacy rate	0.8690***	(0.2074)
Share of SC population	-3.2285***	(1.2165)
Urbanisation	0.2726*	(0.1518)
Intercept	1.4632***	(0. 40271)
Number of observations	4440	

Note: the dependent variable is the logarithm of wages per worker. Robust Standard errors reported in parentheses are clustered at the district level. Sampling weights are used in estimation.
***, **, and * denote significance at the 1,5, and 10 percent levels, respectively. Counterfactual (C) is the estimated wage distribution, showing GI mean wage (or wage gap) if they had the same coefficients as their NGI counterparts. The total composition effect refers to the part of the wage gap due to firm category (GI/NGI) differences in characteristics/endowments. The total structural effect refers to the part of the wage gap due to firm category (GI/NGI) differences in returns to those characteristics. The pure composition effect and pure structural effect are the differences net of specification error and reweighting error, respectively.
Source: Own estimates.

As noted earlier, GI firms pay lower wages than NGI firms. Unlike the coefficient of the structural effect, the coefficient for the composition effect is significant at the 1 percent level, highlighting its importance in explaining the wage gap between GI and NGI firms. Overall, the composition effect reduces the wage gap by about 14 percent. Along with aggregate estimates, Table 5.6 also presents disaggregated estimates. A negative coefficient for a covariate narrows the gap, while a positive coefficient widens it. The disaggregated results show that the wage gap is almost equally influenced by both the pure composition effect and the pure structural effect. To be precise, the pure composition effects narrow the gap by 14 percent, whereas the pure structural effects widen it by 15 percent.

Our disaggregated results show that capital intensity and urbanisation contribute most to the size of the wage gap via the pure composition effect. Differences in capital intensity and the rate of urbanisation between GI and NGI firms narrow the gap by about 10 percent and 0.6 percent, respectively. For pure structural effects, differences in age, literacy, SC population, and urbanisation significantly influence the wage gap. Among the covariates, differences in SC population and age narrow the gap by about 320 percent and 0.6 percent, respectively, while differences in literacy rate and rate of urbanisation widen the gap by about 87 percent and 27 percent, respectively. Other covariates do not significantly contribute to the wage gap via pure structural effects.

Decomposition at unconditional quantiles

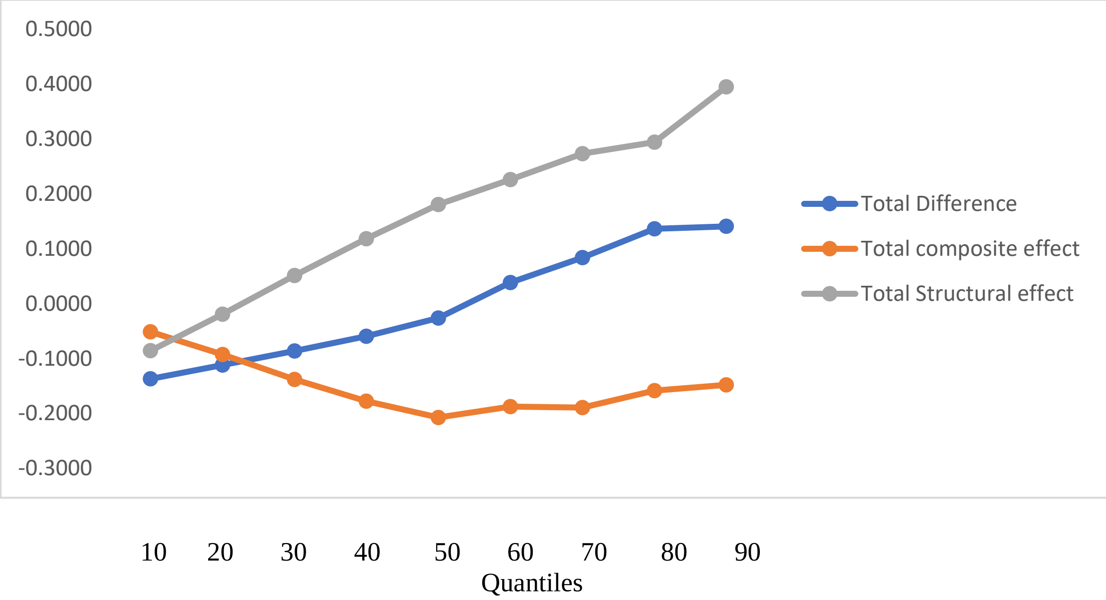
We assess the wage gap at each decile of the wage distribution to understand its evolution and the contribution of each covariate to the composition and structural effects. The results are presented in Table 5.7, with graphical representations in Figures 5.3 to 5.6 and Appendix Figures A5.1 to A5.3. This analysis reveals how the wage gap changes across different levels of the wage distribution, indicating whether it is more pronounced at the lower, middle, or upper ends. By examining the relative importance of different covariates at each decile, we provide a comprehensive view of wage inequality between GI and NGI firms, helping to identify where targeted policy interventions are needed.

Table 5.7: Decomposition of wage gap by percentiles: RIF-Oaxaca detailed decomposition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Overall									
Mean NGI wage per	9.4819***	9.5865***	9.6703***	9.7475***	9.8325***	9.9448***	10.0518***	10.1817***	10.3882***
worker (N)	(0.0261)	(0.0389)	(0.0503)	(0.0637)	(0.0771)	(0.0861)	(0.0807)	(0.0809)	(0.0874)
Mean GI wage per	9.6189***	9.6981***	9.7564***	9.8065***	9.8587***	9.9063***	9.9676***	10.0455***	10.1408***
worker (G)	(0.0053)	(0.0062)	(0.0072)	(0.0087)	(0.0105)	(0.0125)	(0.0172)	(0.0263)	(0.0492)
GI gap in wage (N-G)	-0.1369***	-0.1116***	-0.0860*	-0.0590	-0.0262	0.0384	0.0841	0.1362	0.1408***
	(0.0267)	(0.0394)	(0.0509)	(0.0643)	(0.0778)	(0.0870)	(0.0825)	(0.0851)	(0.0492)
Reweighted decomposition									
Counterfactual (C)	9.5332***	9.6788***	9.8080***	9.9249***	10.0396***	10.1324***	10.2411***	10.3398***	10.5359***
	(0.0316)	(0.0549)	(0.0761)	(0.0846)	(0.0701)	(0.0626)	(0.0522)	(0.05090	(0.0601)
Total composition effect	-0.0512	-0.0923*	-0.1376*	-0.1773**	-0.2071**	-0.1876**	-0.1893***	-0.1581***	-0.1477**
(N-C)	(0.0410)	(0.0564)	(0.0749)	(0.0885)	(0.0865)	(0.0786)	(0.0647)	(0.0534)	(-0.0625)
Total Structural effect	-0.0857**	-0.0192	0.0516	0.1184	0.1808**	0.2260***	0.2734***	0.2943***	0.3950***
(C-G)	(0.0353)	(0.05870	(0.0795)	(0.0871)	(0.0722)	(0.0652)	(0.0558)	(0.0585)	(0.0792)
RIF aggregate decomposition									
Pure composition effect	-0.0274	-0.05657**	-0.0814***	-0.1204***	-0.1647***	-0.2123***	-0.2180***	-0.2184***	-0.2225***
	(0.0216)	(0.0276)	(0.0316)	(0.0348)	(0.0375)	(0.0362)	0(.0392)	(0.0407)	(0.0615)
Specification error	-0.0238	-0.0357	-0.0562	-0.0569	-0.0424	0.0247	0.0286	0.0603	0.0748
	(0.0312)	(0.0390)	(0.0554)	(0.0639)	(0.0584)	(0.0671)	(0.0715)	(0.0678)	(0.0961)
Pure structural effect	-0.0959***	-0.0367	0.0238	0.0832***	0.1513***	0.1996***	0.2506***	0.2720***	0.3693***
	(0.0212)	(0.0273)	(0.0301)	(0.0267)	(0.0241)	(0.0303)	(0.0344)	(0.0359)	(0.0656)
Reweighting error	0.0102	0.0175	0.0277	0.0351	0.0296	0.0264	0.0227	0.0222	0.0257
	(0.0309)	(0.0540)	(0.0754)	(0.0841)	(0.0701)	(0.0638)	(0.0542)	(0.0510)	(0.0612)

Note: The dependent variable is the estimated RIF at the respective decile of the log wages per worker. The GI wage gap is the difference between the log wages paid per worker of NGI firms and GI firms. Sampling weights are used in estimations. Standard errors reported in parentheses are robust to heteroskedasticity and clustered residuals within districts. The reweighting factors are estimated using a logit model. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.
Source: Own estimates. For detail refer to Appendix Table 5.1A.

Figure 5.3: Breakdown of the wage gap by deciles

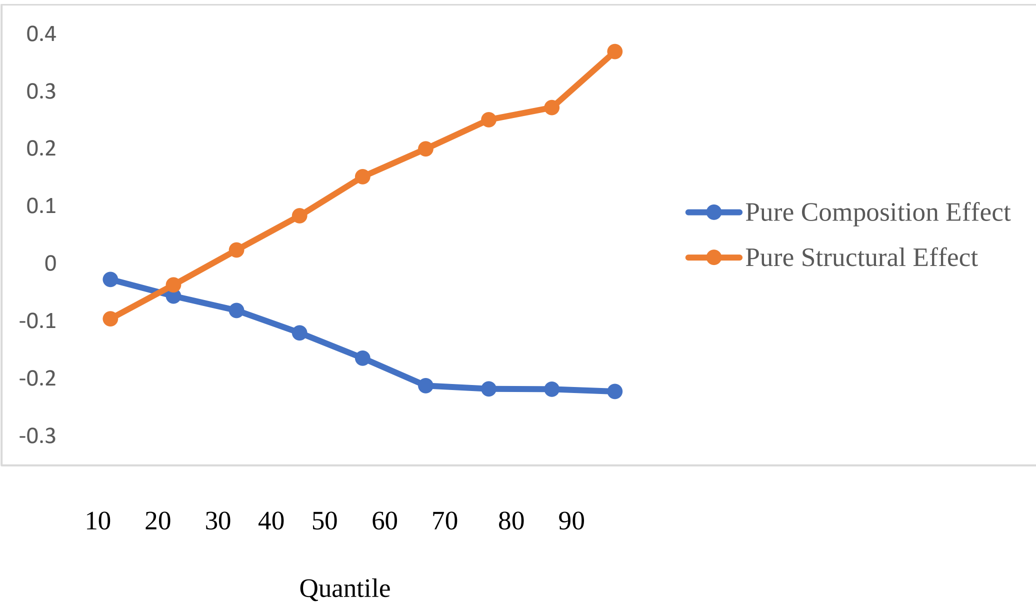


Note: The log difference is between Non-GI (NGI) and GI wage gap. The figure is based on the reweighted RIF-Oaxaca decomposition results presented in Table 5.7 and Table 5.1A.

At the aggregate level, the mean wages of NGI and GI firms increase significantly from the lower to upper deciles, but at different rates (see Table 5.7 and Table A5.1). The wage gap is unevenly distributed (Figure 5.3), being highest at the 90th quantile and lowest at the 30th quantile (Table 5.7). The gap is negative in the early part of the distribution, indicating GI firms pay more than NGI firms, but it turns positive later, indicating NGI firms pay more. The wage gap is significant mainly at the lower and uppermost quantiles. The gap is higher at the top and bottom ends, narrowing in the middle deciles (Table 5.7). Our findings suggest GI firms pay more at the lower deciles, whereas NGI firms pay more at the top end. This shows that GI firms are not always at a disadvantage in the wage gap distribution.

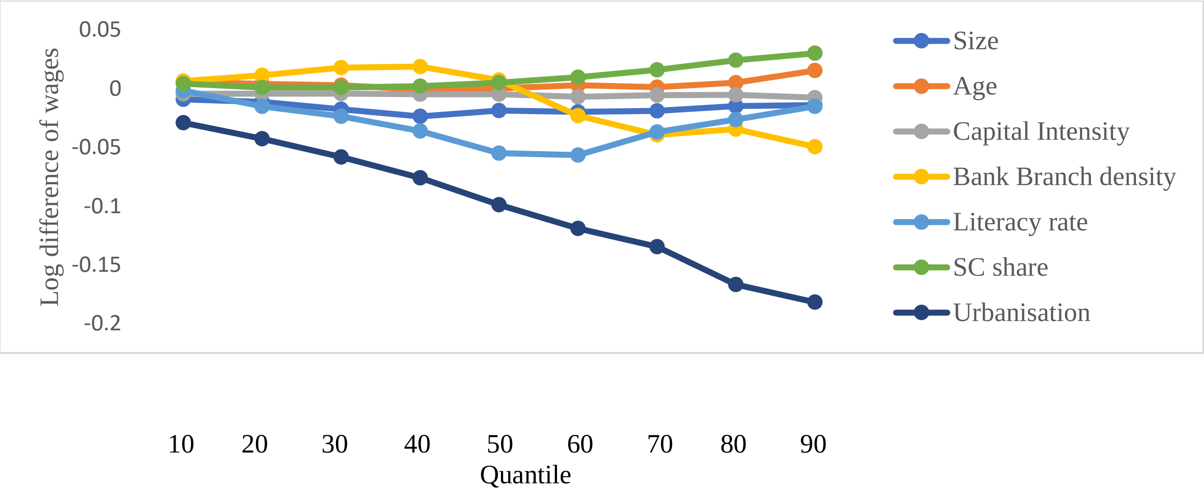
Overall, the RIF decomposition results highlight the importance of investigating the GI-NGI wage gap and its causes across the wage distribution. The average wage gap conceals important subtleties along the wage distribution. To be precise, the gap is unevenly distributed, with NGI-GI productivity differentials growing as we move up the distribution. The key finding is that workers in GI firms benefit more among low-wage-paying firms, while the opposite is true for high-wage-paying firms. As we move up the quantiles, the wage gap increases, suggesting that it is more pronounced in high-wage-paying firms than in low-wage-paying firms. The larger wage gap in the uppermost quantiles is mainly explained by the structural effect, even though the composition effect narrows the gap. Specifically, the wage gap significantly increases due to structural effects, from 18 percent at the 50th decile to 40 percent at the 90th decile. Figure 5.3 illustrates the growing role of structural effects across deciles. The composition effect narrows the wage gap by 9 to 15 percent, but is weaker in the lowermost deciles and improves from the 40th percentile upwards. The rising wage gap is driven largely by structural effects rather than composition effects across the deciles, suggesting that if the variables determining wages yielded similar returns for GI and NGI firms, the wage gap would drop substantially.

Figure 5.4: Detailed RIF Decomposition of Pure Composition and Structural effects



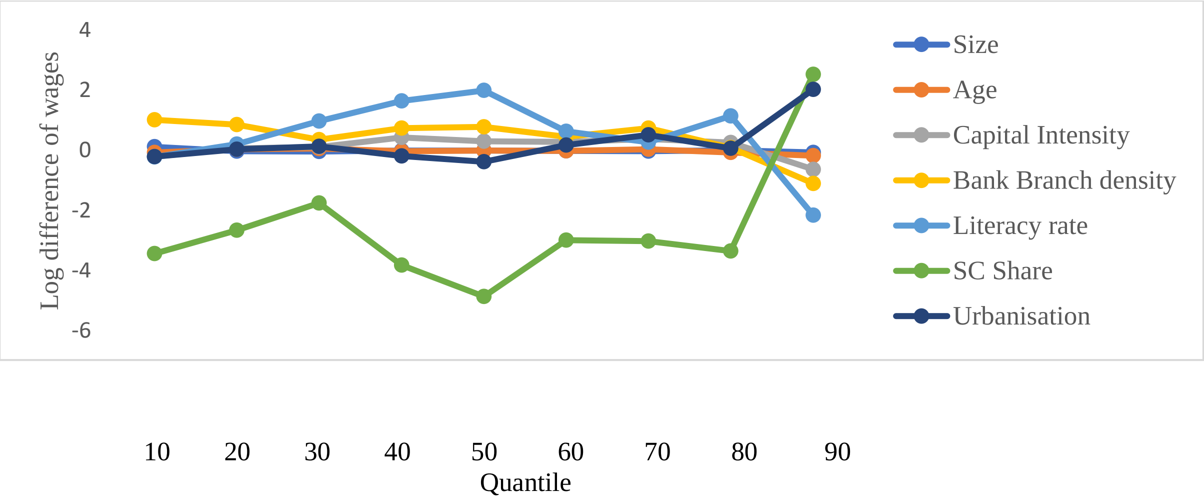
Note: The log difference is between Non-GI (NGI) and GI wage gap. Entries are based on the reweighted RIF-Oaxaca decomposition results presented in Appendix Table A5.1.
Source: Own estimates.

Figure 5.5: Detailed RIF decomposition of the composition effect



Note: The log difference is between Non-GI (NGI) and GI wage gap. Entries are based on the reweighted RIF-Oaxaca decomposition results presented in Appendix Table A5.1.
Source: Own estimates.

Figure 5.6: Detailed RIF decomposition of structural effect



Note: The log difference is between Non-GI (NGI) and GI wage gap. Entries are based on the reweighted RIF-Oaxaca decomposition results presented in Appendix Table A5.1.
Source: Own estimates.

Explaining Wage Differences along the Distribution

Which are the key covariates explaining the wage gap across the deciles? The decomposition of the wage gap into pure composition and structural effects for each decile, shown in Table 5.7 and Figure 5.4, reveals that both effects significantly contribute to the wage gap at almost every decile. The pure composition effect consistently narrows the gap by 3 to 22 percent from lower to upper deciles, with the highest contribution in the 90th decile and the lowest in the 10th decile. In contrast, the pure structural effect widens the gap by 10 to 37 percent across the deciles, with the highest contribution in the 90th decile and the lowest in the 10th decile. Figure 5.4 demonstrates that the pure structural effect plays a larger role in influencing the wage gap than the pure composition effect.

Urbanisation and capital intensity significantly contribute to the wage gap through the pure composition effect at almost every decile (Figure 5.5 and Appendix Table A5.1). The contribution of urbanisation to reducing the wage gap ranges from 10 to 19 percent between the 50th and 90th deciles, while capital intensity narrows the gap by about 1 percent across the wage distribution. Additionally, Figure 5.6 and Appendix Table A5.1 show that the SC share, firm size, and firm age, with negative coefficients, reduce the pure structural effects, whereas literacy, bank branch density, and capital intensity increase the structural effects, thereby expanding the gap.

Overall, our findings based on the RIF decomposition analysis suggest that the wage gap is equally explained by both composition and structural effects, highlighting the importance of addressing both to reduce wage inequality. Policies aimed at improving urbanisation and capital intensity of GI firms could narrow the gap by addressing composition effects. For tea-producing firms located in hilly areas, urbanization could include developing better infrastructure, such as improved road and transportation networks and connectivity to urban markets. This can help enable easier access to resources and markets, boosting productivity and facilitating firms to offer higher wages. Moreover, granting tax incentives for investments in advanced machinery and technology can substantially enhance the productivity of GI firms. Furthermore, ensuring that similar characteristics are equally rewarded in both GI and NGI firms could help mitigate the structural effects contributing to the wage gap.

5.4 Conclusion

This chapter has examined the wage gap between GI and NGI tea manufacturing firms across the wage distribution, using Oaxaca and RIF-Oaxaca decomposition methods. Our RIF analysis revealed significant differences influenced by regional characteristics such as urbanisation, the share of the SC population, and literacy rate, along with firm-specific factors like size and capital intensity. These factors play a crucial role in explaining the wage gap, suggesting that targeted efforts to address these disparities could effectively narrow it.

Our decomposition results showed a narrowing of the wage gap following GI intervention, indicating that GI firms are beginning to offer better wages, particularly benefitting lower-wage workers. This finding aligns with existing literature suggesting that GI adoption can uplift impoverished workers. Importantly, the wage gap widens as we move up the wage distribution, with larger disparities observed in high-wage firms compared to low-wage firms. To be specific, smaller firms paying lower wages seem to benefit more from GI adoption. Moreover, GI firms exhibit higher wages relative to NGI firms in the low-wage category, highlighting the policy relevance of GI and its potential to improve worker conditions.

These findings suggest that effective implementation of GI legislation, combined with efforts to address differences in observable characteristics, could yield substantial benefits for workers over time. In the future, policy efforts should focus on how to extend these benefits to firms across the entire wage distribution continuum.

Achieving this wider impact in the long-term calls for sustained efforts, as benefits from GI adoption may take time to diffuse across all firms. In the next chapter, we will shift our focus from the firm level to the garden level to comprehensively examine the GI effect and capture its impact at various levels.

CHAPTER 6

EMPLOYMENT IMPACT OF GI ADOPTION

6.1 Introduction

In the previous chapter, we discerned a substantial wage gap between GI and NGI firms in the Indian tea industry, identifying several contributing factors. Building on this, we now examine the employment implications of GI registration. One of the core objectives of GI registration is to enhance rural employment and alleviate poverty (WTO, 2004; WIPO, 2021). The Indian tea industry is a major employer in the organized sector (Bhowmik et al., 1996; Saha et al., 2019). Predominantly located in impoverished regions, tea plantations are crucial for rural economic growth and poverty reduction (Sharma et al., 2017; Joseph, 2020; IBEF, 2022; Wang et al., 2023). The garden population often has limited access to the labour market due to inadequate education, remote locations, and insufficient economic opportunities (Bagchi, 1973; ILO, 2010; Sarkar, 2016). Therefore, employment in tea plantations is vital for rural livelihoods, and well-being.

Despite this, research specifically focusing on the employment outcomes facilitated by GIs remains limited, particularly within the Indian context. This chapter aims to fill this gap by addressing the question: Do GIs significantly increase employment opportunities in GI-registered gardens compared to non-GI (NGI) gardens? We seek to understand the influence of GI policy and other factors on employment disparities. Specifically, we investigate whether GI-designated gardens have higher employment levels compared to NGI gardens, and identify the factors driving this employment differential. Understanding these dynamics is crucial for policymakers aiming to leverage GIs for rural development and economic sustainability.

This chapter is organized as follows. Section 6.2 describes the dataset and methods. Section 6.3 presents the empirical results and discussion. The chapter concludes with Section 6.4, summarizing the findings and their implications for policy.

6.2 Data and Method

6.2.1 Data

This chapter uses data from a garden-level survey conducted in 2011-12, covering the Darjeeling and Jalpaiguri districts in the northern region of West Bengal, India. The survey, the first of its kind, was carried out by the Regional Labour Offices (RLOs) under the Joint Labour Commissioner of the North Bengal Zone, Government of West Bengal. The survey encompassed the Darjeeling Hills, Terai, and Dooars regions, dividing tea gardens into eight RLO jurisdictions: Darjeeling, Kurseong, Kalimpong, and Siliguri within the Darjeeling district, and Malbazar, Jalpaiguri, Alipurduar, and Birpara within the Jalpaiguri district.

The survey covered 273 gardens, gathering information on the year of establishment, location, management, workers, trade unions, plantation area, welfare facilities, and access to finance. Following the Tea Board's demarcation, we classified these gardens into 80 GI gardens in the Hills (Darjeeling, Kurseong, and Kalimpong) and 193 NGI gardens in the plains (Siliguri, Malbazar, Jalpaiguri, Alipurduar, and Birpara). After cleaning[21] the dataset, we had 210 gardens, 59 GI and 151 NGI. GI gardens in Darjeeling, Kurseong (including Mirik), and Kalimpong were coded as 1, while NGI

[21] We had to drop some of the closed gardens, missing information on the year of establishment, and ownership types. Please refer to the chapter Data and Method for a detailed discussion.

gardens in the Terai and Dooars regions were coded as 0. This classification is consistent with the literature on protected goods in both Asian and European countries (Van de Kop et al., 2006; Bouamra-Mechemache and Chaaban, 2010; Jena and Grote, 2010; Zhao et al., 2016; Poetschki et al., 2020; Savelli et al., 2021). Important garden characteristics, such as ownership, were extracted from the Tea Directory, West Bengal, published by the Tea Board of India.

Construction of Variables

This section describes the variables used in the analysis and their construction. Table 6.1 provides an overview of the variables used in the study.

Table 6.1: Construction of variables

Variables	Definition
Dependent variable	
Employment per hectare	Ration of total employment (including workers, staff, and managers) to plantation area (in hectares)
Independent variables	
Age	
Young	Dummy variable, 1 if the garden is less than 100 years old, 0 otherwise
Middle-aged	Dummy variable, 1 if the garden is between 100-150 years old, 0 otherwise
Old	Dummy variable, 1 if the garden is more than 150 years old, 0 otherwise
Ownership	Dummy variable, 1 if the garden is a partnership, 0 if it is a proprietorship
Access to computers	Dummy variable, 1 if the garden uses computers, 0 otherwise
Replantation	Dummy variable, 1 if the garden has undertaken replantation activities, 0 otherwise
Housing maintenance expenditure	Costs for repair and upkeep of worker housing per capita for each garden
Access to bank finance	Dummy variable, 1 if the garden has accessed bank finance, 0 otherwise
Access to alternate employment	Dummy variable, 1 if the garden workers have access to public employment guarantee schemes, 0 otherwise
Garden population density	Garden population per hectare
Share of Rural population	Share of rural population in total population at the sub-division (taluka) level

Source: Own construction.

Dependent Variable

As this chapter examines the employment outcomes of GI adoption at the garden level, our dependent variable of interest is garden employment. We measure employment per hectare, calculated by dividing the total number of persons employed by the actual plantation area (in hectares).

Independent Variables

Our main variable of interest is GI adoption. We measure GI status by whether the garden has GI certification. This is a binary variable, assigned a value of 1 for gardens with GI certification and 0 for those without.

Other independent variables in our analysis are divided into garden characteristics and regional characteristics. Garden characteristics include age, ownership, replantation, access to computers, housing maintenance expenditure, access to finance, access to alternate employment opportunities, and garden population density. Age is categorized into young (less than 100 years), middle-aged (100-150 years), and old (more than 150 years). Ownership is a binary variable coded as 1 for partnership gardens and 0 for proprietary gardens. Replantation, a binary variable, indicates whether the garden has undertaken replantation activities in the past year. Replantation is crucial for productivity but may raise costs and affect hiring (Wijerathna and Samaraweera, 2021). Access to computers, another binary variable, captures the use of ICT by tea gardens; investment in IT, such as computers, can impact employment differently, potentially enabling scalability but also introducing automation (Rifkin, 1995; Vashisht, 2018). Housing maintenance expenditure refers to the costs incurred for the repair and maintenance of worker housing in each garden. It is calculated per capita and is used as a proxy for welfare measures. Additional costs associated with these benefits might limit hiring (John and Mansingh, 2013). Access to finance is a dummy variable indicating whether the garden accessed bank finance, which can influence hiring decisions, as firms securing bank finance are likely to expand employment (Beck et al., 2005; Raj et al., 2014; Ergün and Doruk, 2020). Access to alternate employment opportunities is captured through a binary variable, reflecting the availability of other employment options such as Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGA) and Swarnajayanti Gram Swarozgar Yojana (SGRY) in the locality; access to public employment guarantees can impact the garden labor supply and employment (Sen, 2015; Kumar, 2022). Garden population density, measured as the ratio of garden population to garden size, is included to account for the potential labor pool available to the gardens, with higher population densities potentially providing a larger pool of workers. Additionally, regional characteristics are represented by the share of the rural population at the taluka (sub-division) level, which can influence labor supply for the gardens. These variables together represent various aspects of garden operations and regional characteristics, providing a comprehensive analysis of the factors influencing garden employment outcomes.

Descriptive Statistics

Our summary statistics in Table 6.2 indicates that each garden employs around three workers per hectare on average. Of the gardens in our dataset, 76% are partnership gardens, and the rest are proprietary. Approximately 56% of the gardens use computers and other IT infrastructure. On average, 73% of the gardens engage in replantation, and 20% of the workforce is on contract. Management spends around Rs 420 per employee on housing maintenance. About 63% of the gardens have accessed bank finance. Additionally, workers in 30% of the gardens have access to alternate employment opportunities, namely, public employment guarantee schemes such as MGNREGA and SGRY. The population density in the garden areas is approximately 12 persons per hectare, with around 85% of the total population residing in rural areas.

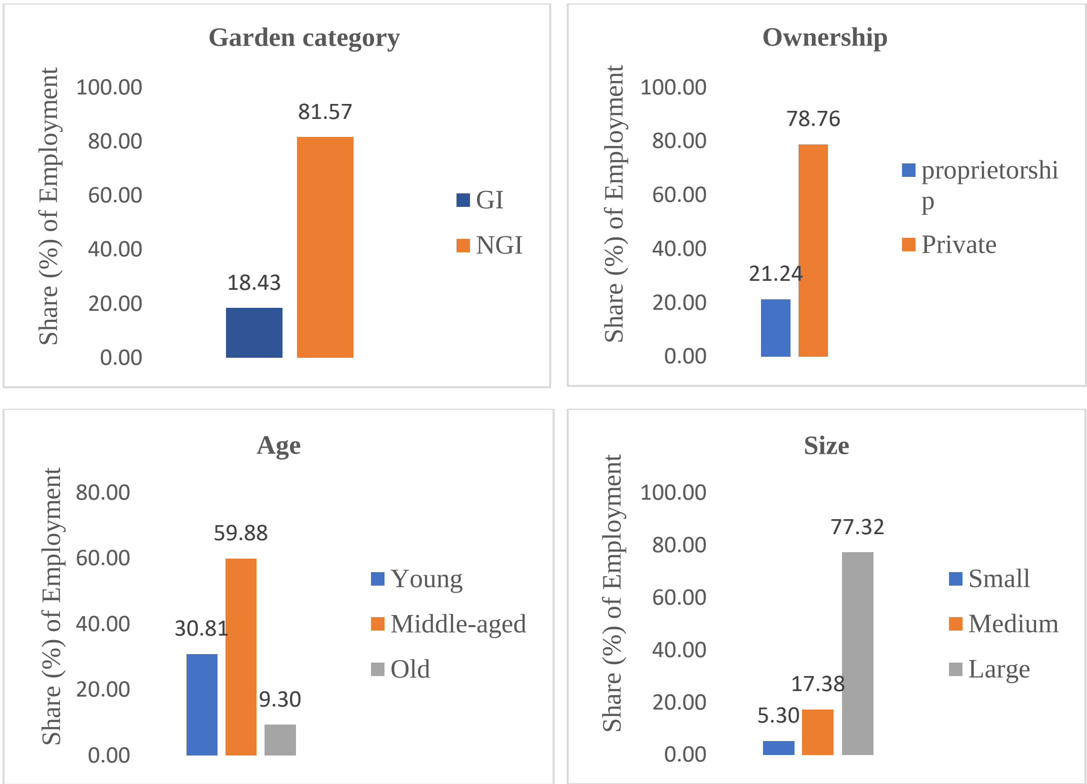
Table 6.2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment per hectare	210	3.2699	0.8937	0.7445	5.9167
Age	210	1.7857	0.6390	1	3
Ownership	210	0.7619	0.4269	0	1
Access to Computer	210	0.5619	0.4973	0	1
Replantation	210	0.7286	0.4458	0	1
Housing maintenance expenditure	210	422.6095	530.8598	0	2971.0313
Access to bank finance	210	0.6238	0.4856	0	1
Access to alternate employment	210	0.2952	0.4572	0	1
Garden population density	210	11.1445	4.6516	0.4395	32.1359
Share of Rural population	210	0.8482	0.0706	0.7245	0.9664

Source: Own estimates.

Figure 6.1 presents the distribution of employment by garden characteristics, namely, garden category, size, age, and ownership. By age, gardens are classified as young (less than 100 years), middle-aged (100 to 150 years), and old (above 150 years). By ownership, gardens are classified as partnership or proprietary. Employment is significantly higher in NGI gardens, which account for over 80% of total employment. Most employment, around 60%, is concentrated in middle-aged gardens. Similarly, large gardens account for about 77% of total employment. About 80% of employment is provided by partnership gardens. This shows that employment varies significantly across garden characteristics, with NGI, partnership, and middle-aged gardens employing a higher share of workers than their counterparts.

Figure 6.1: Employment distribution across the garden characteristics



Source: Own estimates.

6.2.2 Empirical Strategy

Ordinary Least Squares Model (OLS)

We initiate our empirical investigation with the Ordinary Least Squares (OLS) model:

$$Y_i = \beta_0 + \beta_1 GI_i + \beta_2 X_i + e_i \qquad (1)$$

where Yi represents employment, and GI_i indicates whether a garden falls within GI-demarcated areas. Xi is a vector of independent variables, including age, ownership, access to computers, replantation, share of contract workers, housing expenditure per capita, access to bank finance, access to public employment, population density, and share of the rural population. e_i is our error term.

Endogenous Treatment Regression (ETR) Model

Our empirical strategy aims to establish the effect of GI on employment. However, the robustness of our estimation hinges on the exogeneity of the variable representing GI adoption. Endogeneity arises when an explanatory variable correlates with the error term of an outcome. We are concerned that the association between GI adoption and employment may be influenced by omitted variables, selection biases, and reverse causality. Omission of key variables related to both the regressor and dependent variables can bias the estimates. For instance, a garden's decision to hire additional workers may be influenced by managerial ability, pressure from workers' unions, and other unobserved characteristics. Additionally, the decision to apply for GI protection is solely at the discretion of the firm, making it a self-selection process (Poetschki et al., 2021). Simultaneity bias also becomes an issue if gardens with better characteristics, such as reputation, quality-orientation, and large size, are better positioned to access GI adoption. Hence, in the presence of endogeneity, measuring the exact causality between GI adoption and employment becomes challenging. To address this, we employ the Endogenous Treatment Regression (ETR) method using instrumental variables. However, identifying appropriate instruments for GI adoption presents challenges, as highlighted in the literature (Raimondi et al., 2020; Stranieri et al., 2023). In our estimation, we use elevation at the garden level collected from Google Earth, as an instrument for GI adoption. Elevation, measured in meters above sea level, is crucial for tea cultivation due to the sensitivity of the industry to climate and geography (Jairu and Acharya, 2020). Thus, elevation significantly influences the overall operation of the gardens.

Our choice of instrumental variable (IV) is guided by insights derived from existing studies on the GI effect (Husnain et al., 2018; Poetschki et al., 2020; Chandra et al., 2023; Qian et al., 2023; Yin et al., 2024). Elevation stands out as our IV due to its positive influence on tea quality (Han et al., 2017; Chen et. al., 2022). Given that GI protection hinges on geographic attributes and quality, gardens situated at higher elevations are more inclined to produce premium tea and are thus more likely to seek GI status. Consequently, GI producers are often found in elevated or mountainous regions. Importantly, we believe elevation influences employment solely through its impact on GI adoption, meeting the exclusion criteria.

To tackle endogeneity, we employ the Endogenous Treatment Regression (ETR)[22] method. Following Ma et al. (2020), this involves two stages. The first stage utilizes a binary choice model to ascertain whether a garden opts for GI registration, considering factors affecting GI adoption. In the second stage, we model employment (Yi), accounting for factors influencing hiring and controlling for potential endogeneity associated with GI. The first and second stage equations are presented below in equations (2) and (3):

$$First\ stage: GI *_i = \delta_i X_i + \varsigma i IV_i + \varepsilon_i, GI_i = 1, if\ GI_i > 0, \quad (2)$$

$$0, \text{ otherwise},$$

$$Second\ stage: Y_i = \alpha_i GI_i + \beta_i X_i + \mu_i \quad (3)$$

Here, GI^*_i is a latent variable representing the utility difference between GI and non-GI registration for garden i. GI_i is a binary variable indicating GI adoption. Xi comprises factors influencing employment, namely those capturing garden characteristics and regional characteristics, while IV_i represents the instrument(s) for ETR estimation. Parameters to estimate include δi, ςi, α_i, and βi, with α_i capturing the

[22] It is also known as an endogenous binary-variable model or as an endogenous dummy-variable model.

direct effect of GI registration on garden employment. Error terms are denoted by εi and μi.

Exogenous Switching Regression (ESR) Model

We also employ the Exogenous Switching Regression (ESR) model to examine the employment gap induced by GI adoption between GI and NGI gardens. ESR is crucial for identifying the GI effect on employment differences while accounting for observable and unobservable factors in a counterfactual framework. Traditional OLS estimates, including pooled regression assume the same impact of covariates on both treated and untreated groups, providing only the intercept effect (Muricho et al., 2020; Kassie et al., 2013). In contrast, ESR offers slope effects based on treatment, considering all covariates affecting the choice of treatment. Before conducting ESR estimation, we check for homogeneous slopes by garden category using the Chow test. A significant result (3.27 at 1 percent) suggests the need to estimate treatment-specific coefficients using ESR (Aryal et al., 2019).

In the ESR framework, we have separate equations for GI (treated) and NGI (untreated) gardens:

$$Y_{GI} = X_{GI}\beta_{GI} + \mu_{GI} \; if \; G = 1 \qquad (4a)$$

$$Y_{NGI} = X_{NGI}\beta_{NGI} + \mu_{NGI} \; if \; G = 0 \qquad (4b)$$

Here, subscripts GI and NGI denote GI and NGI gardens, respectively, with G representing our treatment (GI) dummy (GI =1, NGI = 0). Y is the outcome variable (employment per hectare), and X and β are vectors of explanatory variables and coefficients, respectively. The term u is a random error term with zero mean and constant variance.

The impact of GI on employment is assessed through a counterfactual scenario[23], estimating the employment levels of GI gardens if their returns were the same as NGI gardens, and vice-versa. This comparison enables the identification of the treatment effect (GI) on employment. We illustrate this with the following equations:

$$E\ (Y_{GI} \mid G = 1)\ =\ X_{GI}\beta_{GI} \qquad (5a)$$

$$E\ (Y_{NGI} \mid G = 0)\ =\ X_{NGI}\beta_{NGI} \qquad (5b)$$

$$E\ (Y_{NGI} \mid G = 1)\ =\ X_{GI}\beta_{NGI} \qquad (5c)$$

$$E\ (Y_{GI} \mid G = 0)\ =\ X_{NGI}\beta_{GI} \qquad (5d)$$

Equations (5a) and (5b) represent observed employment levels of GI and NGI gardens, while equations (5c) and (5d) represent their counterfactual expected employment levels. Table 6.3 demonstrates how these conditional expectations, combined with the GI treatment variable allow for the calculation of the treatment effect on employment.

[23] For details on ESR, please refer Carter and Milon (2005).

Table 6.3: Conditional Expectations, Treatment, and Heterogeneity effects

Firm category	Decision stage		Treatment effects
	To adopt GI	**Not to adopt GI**	
GI gardens	$E(Y_{GI} \mid G=1) = X_{GI}\beta_{GI}$ (6a)	$E(Y_{NGI} \mid G=1) = X_{GI}\beta_{NGI}$ (6c)	ATT = (6a - 6c)
NGI gardens	$E(Y_{GI} \mid G=0) = X_{NGI}\beta_{GI}$ (6d)	$E(Y_{NGI} \mid G=0) = X_{NGI}\beta_{NGI}$ (6b)	ATU= (6d - 6b)
Heterogeneity effect (difference due to unobserved characteristics)	BH_{GI} = (6a - 6d)	BH_{NGI}= (6c - 6b)	TH = (6a - 6b)

Note: ATT is the average treatment effect on the treated.
TTU is the average treatment effect on the untreated.
BH is the base heterogeneity.
TH is transactional heterogeneity.
5a, 5b, 5c, and 5d represent the equations listed earlier.

6.3 Results

We now move on to discuss the estimation results. We first discuss the baseline estimation of determinants of garden employment using OLS. Then, we discuss our main estimation results, including the ETR and ESR findings.

6.3.1 Baseline Results

Table 6.4 presents the OLS estimates. Column 1 reports results for pooled data, combining GI and NGI gardens. Columns 2 and 3 provide GI-specific results, with column 2 showing estimates for GI gardens and column 3 for NGI gardens. The coefficient for GI in column 1 is positive and significant, indicating that GI gardens tend to hire more workers than NGI gardens. To be specific, GI gardens employ approximately 33% more workers than NGI gardens, translating to about 1 additional worker per 3 hectares of plantation area. However, this pooled regression captures only an intercept shift, as covariates exert uniform influence across GI and NGI gardens without interacting with GI status. To isolate the causal effect of GI on employment, separate estimations for GI and NGI gardens were conducted.

Consistently across both pooled and GI-specific estimations, population density shows a positive effect on employment, suggesting that higher population areas facilitate greater workforce recruitment. The coefficient of ownership variable is positive and significant in the pooled estimation, indicating higher employment levels in partnership gardens compared to proprietary ones. In GI-specific estimations, this positive relationship is evident only among NGI gardens, while in GI gardens, the coefficient, though positive, is insignificant. Partnership gardens are likely to outperform small proprietorship ones in hiring due to superior management and financial access. Replantation activity emerges as a significant driver of employment, particularly in GI gardens. As expected, increased financial access has a positive impact on employment, supporting the notion that firms with bank finance tend to expand their workforce more rapidly.

Contrary to expectations, a higher share of the rural population is negatively correlated with employment levels in GI gardens. This could be attributed to the specific knowledge, skills, and experience required in GI recruitment, which may not align with the attributes of a growing rural population (WIPO, 2021). While OLS identifies factors influencing employment across garden categories, it does not address endogeneity concerns, potentially contaminating the results. In the next section, we discuss the results of ETR and ESR estimations, where we address these concerns.

Table 6.4: Determinants of employment: OLS estimation

Independent Variables	Dependent Variable: Employment per hectare		
	All gardens	GI gardens	NGI gardens
	(1)	(2)	(3)
GI	0.3329*	-	-
	(0.1834)		
Age			
Middle-age	-0.0497	-0.3023	-0.0170
	(0.1380)	(0.3871)	(0.1541)
Old	-0.2161	-0.3760	-0.6471
	(0.2474)	(0.4029)	(0.6822)
Ownership	0.3044**	0.1274	0.3532*
	(0.1412)	(0.1888)	(0.1907)
Access to Computer	-0.0520	-0.1870	-0.0991
	(0.1214)	(0.1889)	(0.1544)
Replantation	0.1291	0.4402**	0.1144
	(0.1406)	(0.1825)	(0.1929)
Housing maintenance expenditure	0.0041	-0.0141	-0.0106
	(0.0236)	(0.0306)	(0.0334)
Access to bank finance	0.2658**	-0.3795	0.4525***
	(0.1250)	(0.1908)	(0.1587)
Access to alternate employment	-0.1614	0.1565	-0.1845
	(0.1436)	(0.1855)	(0.2082)
Garden population density	0.0679***	0.0831***	0.0658***
	(0.0135)	(0.0179)	(0.0178)
Share of rural population	-0.9073	-10.5273***	-0.4007.
	(0.8931)	(2.6103)	(1.0277)
Constant	2.8091***	11.8501***	2.3456***
	(0.7437)	(2.3720)	(0.8585)
Number of Observations	210	59	151
R-squared	0.1745	0.4740	0.1662

Notes: Standard errors are reported in the parenthesis; *** p<0.01, ** p<0.5, * p<0.10
Source: Own estimates.

6.3.2 ETR Results

To address the possible endogeneity concerns with the GI variable, we employed the ETR estimation. Our GI adoption variable is instrumented using garden elevation. The ETR estimates are presented in Table 6.5, with the first stage results in column 2 and the second stage results in column 3. The various test statistics indicate that the ETR procedure is effective in our estimation. The correlation coefficients of the error terms between the selection equation and the outcome equation, $\rho_{\varepsilon\mu}$, significantly differ from zero, revealing endogeneity from unobserved factors (Hübler and Hartje, 2016). According to Ma et al. (2020), a statistically significant coefficient of $\rho_{\varepsilon\mu}$ indicates an endogeneity issue with the GI adoption variable. The Wald test for $\rho_{\varepsilon\mu}=0$ is also statistically significant, rejecting the null hypothesis of no correlation between the GI specification and outcome specification. This confirms GI adoption as an endogenous variable in the employment specification, addressed through IV estimation (ETR). A positive and significant coefficient on elevation in the first stage regression indicates that higher elevation gardens are more likely to pursue GI protection.

The second stage results in Table 6.5 corroborate the main findings from the OLS estimates. GI gardens consistently employ more workers compared to their NGI counterparts, averaging an additional 0.45 employees per hectare, which translates to approximately 1 additional worker per 2 hectares. The coefficients of the control variables remain consistent with those in the OLS estimates, further reinforcing the robustness of our findings. Importantly, the positive impact of GI adoption on employment aligns with prior research (Rocha et al., 2004; Bouamra-Mechemache, 2012), underscoring the reliability of our results.

Table 6.5: Impact of GI on welfare: ETR model estimation

Independent Variables	Dependent variable	
	GI	Employment per hectare
(1)	(2) First stage	(3) (ETR)
GI	-	0.4566*** (0.1655)
Age		
Middle-age	-0.0589* (0.0317)	-0.0828 (0.1403)
Old	0.1118** (0.0553)	-0.2950 (0.2222)
Ownership	0.0651** (0.0313)	-0.2950 (0.2222)
Access to Computer	-0.0090 (0.0271)	-0.0604 (0.1195)
Replantation	-0.0346 (0.0314)	0.1272 (0.1440)
Housing maintenance expenditure	0.0022 (0.0052)	0.0007 (0.0219)
Access to bank finance	-0.0485* (0.0276)	0.2436** (0.1130)
Access to alternate employment	0.0653** (0.0316)	-0.1850 (0.1334)
Garden population density	0.0048 (0.0030)	0.0673*** (0.0155)
Share of rural population	0.0296 (0.2009)	-0.9351 (0.9055)
Elevation (log)	0.4034*** (0.0200)	-
Constant	-2.0712*** (0.1698)	2.8580*** (0.7679)
Number of Observations	210	210
$\rho_{\varepsilon\mu}$	-0.5291*** (0.1521)	-
Wald test ($\rho_{u\varepsilon}$=0) $\chi2$ (1) =12.10, *prob*>χ^2 = 0.0005		

Note: Standard errors are reported in the parentheses; *** p<0.01, ** p<0.05, * p<0.10
Source: Own estimates.

6.3.3 ESR Results

Our ESR estimation, depicted in Table 6.6, confirms the treatment effect discussed earlier in Table 6.3. It reveals a significant positive impact of GI on both GI and NGI gardens, as indicated by their ATT and ATU values. This implies that GI adoption substantially increased employment for GI gardens, while NGI gardens could have also experienced significant employment growth if they had adopted GI.

Table 6.6: Treatment Effects

Firm category	**Decision stage**		**Treatment Effect**
	To adopt GI	**Not to adopt GI**	
	GI	**NGI**	
GI	3.34	2.85	0.49*** (ATT)
NGI	3.79	3.16	0.63*** (ATU)
Heterogeneity effect	-0.45	-0.31	0.18*** (TH)

Source: Own estimates.

A closer examination of Table 6.6 shows that GI gardens exhibit marginally higher employment growth, about 3.34 employees per hectare, compared to NGI gardens, which have approximately 3.16 employees per hectare. This indicates that GI gardens employ about 0.18 more employees per hectare on average. Without GI adoption, GI gardens' employment growth would have been lower at 2.85 employees per hectare, suggesting that GI registration has led to additional employment. Similarly, NGI gardens, with an actual employment growth of 3.16 employees per hectare could have achieved higher growth, estimated at 3.79 employees per hectare, if they had opted for GI treatment. This underscores the missed employment opportunities for NGI firms by not adopting GI protection.

Furthermore, our estimation reveals heterogeneous effects of GI across GI and NGI gardens, indicating that employment differences stem from inherent factors rather than GI treatment alone. Base heterogeneity suggests that employment variations are intrinsic, while transitional heterogeneity highlights a more significant impact of GI on employment for gardens with GI adoption. In sum, GI adoption has benefited employment in GI gardens and would have positively influenced hiring in NGI gardens had they opted for it. The consistency between the ESR estimation (ATT) and ETR estimation (Table 6.5) underscores the reliability of our findings. Our results are robust in addressing endogeneity concerns.

6.3.4 Robustness Check

Robustness checks in Table 6.7 further validate our findings by focusing on specific sub-samples of gardens. To be precise, we employ ETR on two distinct sub-groups: gardens aged ≥100 years (n=140) and gardens employing more than 500 employees (n=174). In both cases, we observe a positive and statistically significant coefficient for GI adoption, suggesting that GI registration positively impacts employment, consistent with our results in Table 6.5. Across these sub-samples, the results from Table 6.5 and Table 6.7 consistently demonstrate a positive GI effect, estimating approximately 1 additional worker for every 2 hectares, thus reinforcing the robustness of our main findings.

Table 6.7: Sample split Analysis: ETR Results

Independent Variables	Only with gardens aged >= 100 years	Only with gardens employing >500 employees
	Dependent Variable: Employment per hectare	
GI	0.3415* (0.1892)	0.4578** (0.1860)
Age		
Middle-aged	-	-0.1875 (0.1423)
Old	-0.148 (0.1890)	-0.2059 (0.2587)
Ownership	0.2822** (0.1282)	0.2828 (0.1467)
Access to Computers	-0.1821 (0.1269)	-0.2186 (0.1467)
Replantation	0.2089 (0.1682)	0.1114 (0.1506)
Housing maintenance expenditure	0.0101 (0.0239)	0.0212 (0.0246)
Access to bank finance	0.1908 (0.1291)	0.2748 (0.1265)
Access to alternate employment	-0.081 (0.1429)	-0.1695 (0.1461)
Garden population density	0.0580*** (0.0172)	0.0464 (0.0138)
Share of rural population	-1.4423 (1.0711)	-1.0912 (0.8893)
Constant	3.3516*** (0.9155)	3.4051 (0.7604)
Number of Observations	140	174

Note: Standard errors are reported in the parentheses; *** p<0.01, ** p<0.05, * p<0.10
Source: Own estimates.

6.4 Conclusion

This chapter probed the employment implications of GI adoption in the Indian tea industry. Analysing garden-level data from West Bengal, our results highlight the crucial role of GI adoption in enhancing employment. We find strong evidence that GI gardens hire more workers than NGI gardens, employing approximately one additional worker per two hectares. Our empirical results are robust to different specifications, and alternate methods and also to concerns arising from reverse causality. Both our main identification strategy—Instrumental Variable approach using ETR—and the OLS method yield similar results. The findings are consistent when using ESR and split sample analysis.

Our results align with the overarching goal of the GI policy, which aim to stimulate rural employment and income generation. The significant role of GIs in enhancing rural employment is especially pertinent within the predominantly rural tea industry in India. This contribution is crucial in a developing country like India, where rural populations often face economic disparities despite overall economic growth. Furthermore, our study suggests broader policy implications for GI legislation, extending beyond the tea industry. The increasing trend of GI registration for various Indian products indicates the potential for employment generation across diverse sectors. Our empirical evidence supports the promotion of GIs as facilitators of employment creation, consistent with existing literature and international agreements.

In Chapter 7, we shift our investigation from the garden level to the worker level, probing another critical aspect of GI intervention: labour welfare.

CHAPTER 7

GI AND WELFARE OUTCOMES

7.1 Introduction

In the previous chapter, we investigated the impact of GI registration on employment and found that it tends to increase employment opportunities. Equally important is understanding the welfare implications of GI, which aims to enhance welfare through higher income and improved conditions for workers contributing to quality (Bramley et al., 2009; WIPO, 2011).

Examining the welfare impact of GI is crucial, particularly in the tea industry, which is a major livelihood source for workers in underdeveloped regions of India (Joseph, 2020; IBEF, 2022). These workers face significant economic and social challenges, including low wages, harsh working conditions, and inadequate infrastructure (TISS, 2009; Bhowmik, 2015; Sen, 2015; OXFAM, 2019). The GI policy aims to uplift rural living standards by enhancing income, employment, and economic opportunities, thereby alleviating poverty (Dupont, 2003; Desbois and Néfussi, 2007; Isler, 2007; Suh and MacPherson, 2007; Jena et al., 2015; UNCTAD, 2015). Thus, examining the welfare effects of GI at the worker level is imperative.

This chapter investigates the impact of GI on workers' consumption and its contributing factors, with a focus on tea gardens in the Darjeeling district of West Bengal, India. We provide insights into consumption differences induced by GI adoption and the heterogeneity in its effects among workers.

This chapter comprises four sections. Section 7.2 discusses the data and methods. Section 7.3 presents the empirical results. Section 7.4 concludes.

7.2 Data and Methods

7.2.1 Data

Our analysis is based on primary survey data collected from garden workers in the Darjeeling, Kurseong, and Siliguri sub-divisions of the Darjeeling district in West Bengal, India. A pilot survey was conducted in 2022, involving one garden each from GI and NGI regions with 30 workers, enabling us to refine the survey process for full-scale administration in 2023. West Bengal accounts for approximately 25% of the total Indian tea plantation area and 30% of tea production (Tea Board of India, 2021; 2022).

We collected data from a pool of 200 workers, with 100 workers each from the GI and NGI regions, using a Stratified Random Sampling technique. Under this technique, the population is classified into different sub-groups, or strata, based on certain characteristics. Samples are drawn randomly from each stratum, either proportionally or equally. We constructed strata based on the locations of the gardens in the Darjeeling district. Gardens located in the Darjeeling sub-division (hills) form the GI stratum, while gardens in the Siliguri sub-division (plains) form the NGI stratum.

We then selected five gardens each from the GI and NGI regions based on characteristics such as size (area of plantation) and age. We included some of the largest and smallest gardens, as well as some of the oldest and youngest gardens. Then, we employed an equal stratified sampling technique to interview 20 random respondents from each stratum. This resulted in a total of 200 respondents: 100 from GI gardens and 100 from NGI gardens. Figure 7.1 presents a flowchart displaying the steps undertaken to collect the data from the primary survey.

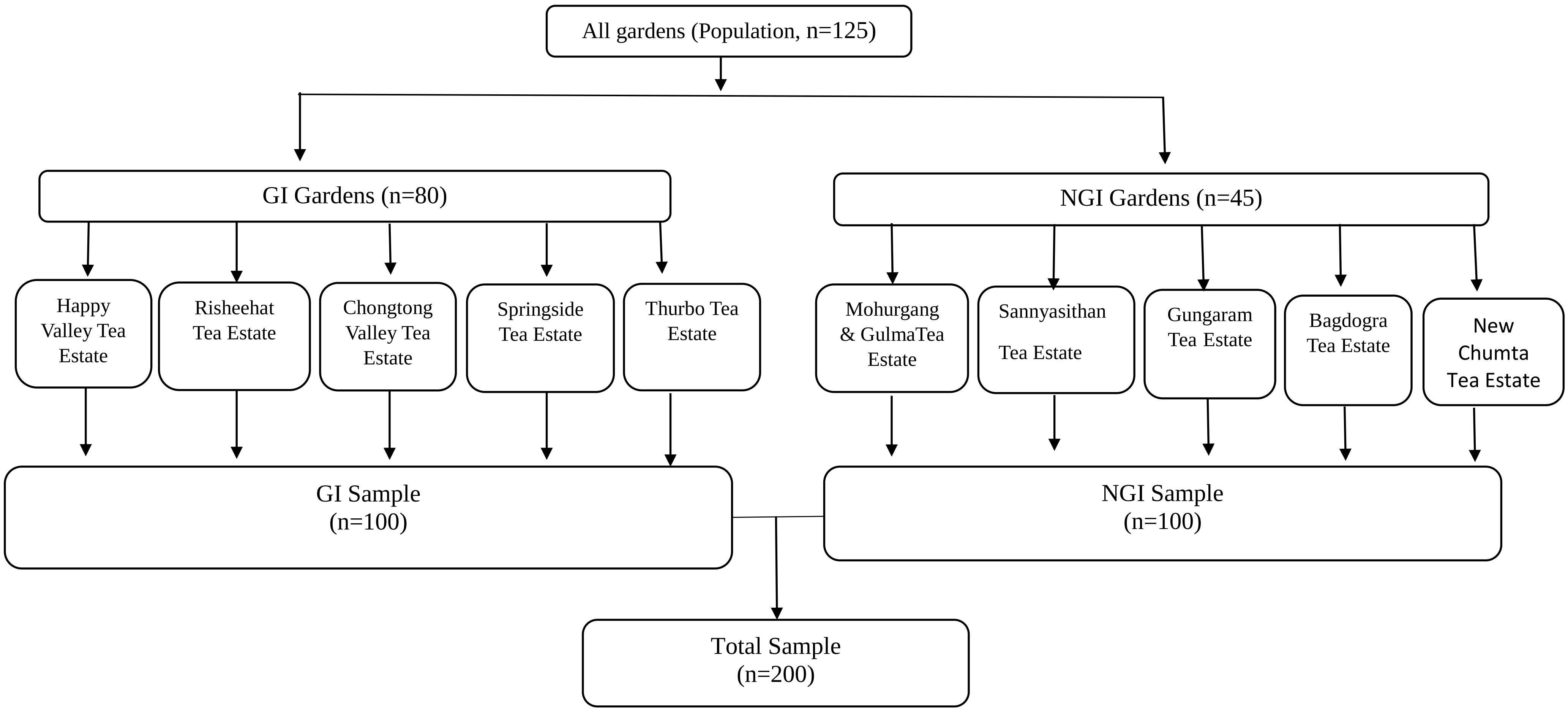
The GI gardens, as demarcated by the Tea Board of India, include the Darjeeling Hills: Darjeeling, Kurseong, and Kalimpong. The gardens situated in the Terai and Dooars regions are labeled as NGI gardens. The selected GI gardens include Happy Valley Tea Estate, Risheehat Tea Estate, and Chongtong Tea Estate in Darjeeling; and Springside Tea Estate and Thurbo Tea Estate in the Kurseong sub-division. The NGI gardens include Mohurgong & Gulma Tea Estate, Sannyasithan Tea Estate, Gungaram Tea Estate, Bagdogra Tea Estate, and New Chumta Tea Estate, located in the Terai region.

The interviews were conducted using a structured questionnaire[24] covering demographic attributes, wages and remuneration, other income sources, consumption, education, health, fringe benefits[25], and job satisfaction, focusing on welfare aspects to capture changes in welfare measures. Information on these variables was collected for both the pre- and post-GI periods. The objective is to designate workers in the GI gardens as the treatment group and workers in the non-GI (NGI) gardens as the control group. A similar strategy was employed by Jena and Gorte (2010) in the case of Basmati rice in Northern India.

[24] For the questionnaire, please refer to the Appendix section

[25] Fringe benefits are non-monetary perks provided by the management to workers, typically including items such as tea, firewood, umbrellas, and field equipment.

Figure 7.1: Flowchart for the primary survey among the target group of tea garden workers



Source: Own construction.

Construction of Variables

The primary objective of this chapter is to evaluate the welfare differences between GI workers and NGI workers, and to identify the factors contributing to these differences. In this section, we outline the construction of the variables used in our analysis. Table 7.1 provides a description of these variables.

Table 7.1: Construction of variables

Variables	Definition
Dependent Variable	
Consumption per capita	Per capita household consumption expenses (in Rs) on food, clothing, education, health, and durable goods
Independent Variables	
GI	Dummy variable for workers in GI gardens (1 for those who work in GI gardens, 0 for those who do not)
Female	Dummy variable for female workers
Age	Age of the workers (in years)
Social group	
General	Dummy variable for General category workers
ST	Dummy variable for ST category workers
SC	Dummy variable for SC category workers.
OBC	Dummy variable for OBC category workers.
Education	Number of years of schooling
Asset Index	Index for asset possession by a worker, considering two assets: TV set and mobile phone. Each asset is assigned an equal weight. The index value ranges from 0 to 2.
Family size	Number of family members.
Employed household members	Dummy variable that takes the value 1 if the worker has any family member in employment, 0 otherwise
Distance to city (km)	Distance between a worker's residence and the main city

Source: Own construction.

Dependent Variable

The key measure we use to proxy worker welfare is consumption per capita. We prefer consumption over income because evidence suggests that income inequality and consumption inequality do not always align; an increase in income inequality does not necessarily lead to higher consumption inequality (Krueger and Perri, 2002).

Thus, consumption is increasingly used as a measure of well-being (Cutler and Katz, 1991; Ma et al., 2020; Chunfang et al., 2023).

Independent variables

Our measure of GI status is straightforward, based on whether the garden where the workers are employed has GI certification. We construct a binary variable for GI status, assigning a value of 1 for workers in GI gardens and 0 for those in NGI gardens.

Several factors influence workers' well-being (OECD, 2023), so we control for these in our analysis. These factors include various individual-level characteristics such as gender, age, social group, education, asset index, family size, having employed household members, as well as regional characteristics like the distance to the nearest city (Table 7.1).

Gender is a categorical variable with females coded as 1 and males as 0. Gender is significant in the tea industry and affects consumption patterns, as women workers are central to the industry (Rasaily, 2014), and gender differences in consumption expenditure are well-documented (Blumberg 1988; Khan and Khalid, 2012; O'Donoghue et al., 2024).

Worker age is a continuous variable representing the age of the workers in years. Consumption expenditure varies by age, and among low-income earners, there is often a negative relationship between age and food security (Bashir et al., 2012). In tea gardens, older workers are particularly vulnerable to food insecurity due to inadequate retirement benefits and abrupt garden closures (National Commission for Scheduled Tribes, 2009; Besky, 2014; EPW, 2014; Sen, 2015).

Social group is a four-way categorical variable representing workers' social backgrounds as General, ST, SC, and OBC. The Indian tea industry has a long history of employing tribal communities (Labour Bureau, 2008-09; Sen, 2015; Das, 2023), who have been exploited and subjected to poor socio-economic conditions since the British Raj, leading to a low dietary intake (Biswas et al., 2005; Das, 2020). It is important to examine the influence of social groups on consumption.

Education is a continuous variable measured by the number of years of schooling of the respondents. Higher education levels are associated with increased consumption expenditure, indicating that education positively impacts consumption (Michael, 1975; Cheng, 2021). Education also affects consumer perceptions and demand for goods and services (Hartley, 2012).

Asset index represents ownership of assets such as television sets and mobile phones, indicating economic status and influencing consumption expenditure. This index is constructed by assigning equal weight to both assets, with values ranging from 0 to 2.

Family size represents the number of members in the family. It has a positive effect on consumption; meaning that with every additional family member consumption increases (Dornbusch et al., 2004; Kiran and Dhawan, 2015).

Employed household members is a binary variable indicating whether the family has an employed member. It takes the value 1 if at least one family member is employed.

Distance to the city is a continuous variable measured in kilometers from the workers' garden residences to the nearest main city. This distance is important as it influences transportation costs, price dispersion, and ultimately consumption (Ahmad and Rustogi, 1987; O'Connell and Wei, 1997; Minten and Kyle, 1999; Zant, 2018; Casaburi et al., 2013; Cai et al., 2022). Proximity to the city generally leads to lower price levels (Melchoir, 2016).

By including these control variables, we aim to account for their influence on workers' welfare and provide a clearer understanding of the factors contributing to consumption differences.

Descriptive statistics

Table 7.2 presents the summary statistics. GI workers make up about 47% of the sample, while the remaining 53% work in NGI gardens. On average, per capita monthly consumption is around Rs 1,800. The average age of workers is around 45 years, with over 75% being female. The majority of workers belong to the ST category. The average education level is below primary school, and 33% of workers own TV sets and mobile phones. For around 52% of workers, tea wage income[26] is their principal income source. Moreover, around 80% of workers have employed family members. The average distance to the main market is around 35 km.

Table 7.2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Consumption	177	1779.156	524.406	900	3000
GI	177	0.469	0.500	0	1
Female	177	0.757	0.430	0	1
Age	177	45.356	7.008	27	58
Social group	177	2.372	1.048	1	4
Education	177	3.508	3.010	0	10
Index of Asset	177	0.328	0.538	0	2
Family size	177	4.616	1.033	3	9
Employed household member	177	0.802	0.399	0	1
Distance to city	177	34.356	24.484	8	72

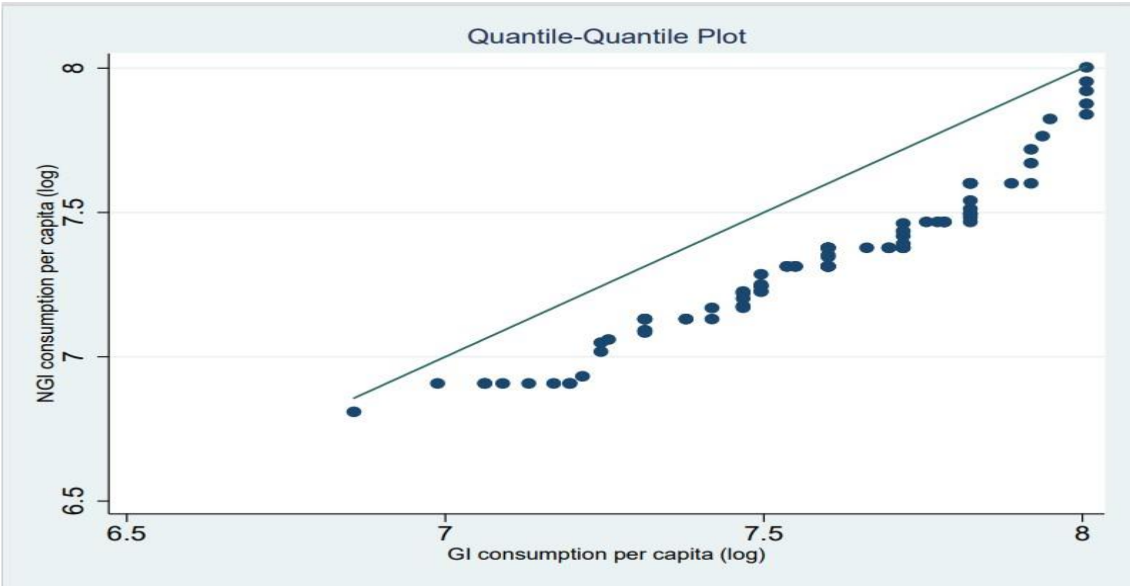
Source: Own estimates

[26] Tea wage income is the primary income source for workers who rely primarily on earnings from their employment in the tea industry.
.

Consumption Distributions

We compare the consumption differences between worker groups using a quantile-quantile plot (Figure 7.2). The plot shows that GI workers' consumption spending is higher than that of NGI workers, suggesting a welfare-enhancing effect. However, a deeper econometric investigation is required, which we undertake in the following section.

Figure 7.2: Consumption by workers group



Source: Own estimates.

7.2.2 Methods

Our empirical investigation begins with an OLS model, which is specified as follows:

$$Y_i = \beta_0 + \beta_1 GI_i + \beta_2 X_i + e_i \qquad (1)$$

where, Yi is the dependent variable, namely, consumption per capita. Our main variable of interest is GI_i, a binary variable that takes the value of 1 if a worker is employed in a GI garden and 0 otherwise. X_i represents a vector of independent variables as defined in Table 7.1, controlling for their influence on our core result. e_i is the error term.

While the OLS model provides a basic framework, our analysis must address potential biases arising from omitted variables, selection, and reverse causality. Key variables related to both the regressor and the dependent variable, if omitted, can skew the estimates. Moreover, consumption decisions may be influenced by workers' psychological attributes, social and cultural norms, and other unobserved characteristics.

The decision to apply for GI protection is made at the firm's discretion, representing a form of self-selection (Poetschki et al., 2021). Bias arises when gardens with superior attributes, such as reputation, quality focus, and larger size, are more likely to adopt GI. This complicates establishing causal relationships between GI adoption and consumption using OLS estimation alone.

To address this endogeneity, we employ the Instrumental Variable Treatment Regression (IVTR) model, drawing inspiration from Cerulli (2014). This approach mitigates endogeneity by treating the binary treatment variable (GI) as endogenous and using elevation[27] as our instrumental variable. This allows us to investigate both the determinants of GI registration and its impact on workers' consumption expenditure while controlling for both observable and unobservable factors.

The IVTR model offers a more comprehensive understanding of the mean effect of GI on consumption. Additionally, we employ Unconditional Quantile Regression (UQR) based on Instrumental Variable Quantile Regression (IVQR) to explore heterogeneous effects of GI across the consumption distribution.

[27] For more on the usage of Elevation as our IV, refer to Chapter 6.

This comprehensive analytical framework addresses potential biases and provides robust insights into the nuanced relationship between GI registration and workers' consumption, thereby enhancing the credibility and reliability of our findings.

IVTR Model

The Instrumental Variable Treatment Regression (IVTR) model allows us to measure causal policy impacts using counterfactual evidence, making it particularly robust for capturing endogenous binary treatment effects (Cerulli, 2014). This model accounts for the non-random assignment to treatment due to firms' selection or external factors.

For each individual, we have potential outcomes (y_1, y_0), where y_1 represents the outcome when the individual is treated, and y_0 represents the outcome when they are not. We collect an independent and identically distributed sample of observations (y_i, w_i, x_i) with i = 1,...,N, where x is a row vector of covariates hypothesized to influence the non-random assignment to treatment. The model assumes:

$$y_0 = \mu_0 + x\beta_0 + e_0, E(e_0) = 0, E(e_0|x) = 0, \mu_0 = parameter \qquad (2)$$

$$y_1 = \mu_1 + x\beta_1 + e_1, E(e_1) = 0, E(e_1|x) = 0, \mu_1 = parameter \qquad (3)$$

$$y = y_0 + \omega(y_1 - y_0) \qquad (4)$$

Equations (2) and (3) are potential outcome equations assumed to be linear in parameters. Equation (4) is the potential outcome model. Additionally, the equation for treatment, w, is:

$$\omega = \theta_0 + x\theta_1 + \alpha \qquad (5)$$

The variable w becomes endogenous when it is correlated with the regression error term, occurring when the error term of the treatment equation is correlated with e_0 or with e_1. Instrumental variables (IVs) can restore consistency under the selection-on-unobservable assumption. Applying IV requires at least one variable z—the instrumental variable—that is directly correlated with treatment w and uncorrelated with the outcome y, satisfying the exclusion restriction to identify causal parameters. In our chapter, we employ IV treatment regression using direct Two-Stage Least Squares (2SLS) regression as presented by Cerulli (2014).

We use elevation (in meters) as our instrument. The elevation of each garden was obtained via Google Earth. Elevation serves as our IV because it influences the quality of tea production (Han et al., 2017; Chen et. al., 2022). GI protection is often granted for exclusivity based on geographic attributes. Therefore, firms located at higher elevations, producing higher quality tea, are more likely to apply for GI protection than other firms.

By adopting IVTR, we utilize elevation as an instrumental variable to control for unobserved factors that may influence both the decision to adopt GI and consumption patterns. This approach allows us to isolate the true effect of GI on workers' consumption, ensuring that our results are not confounded by endogeneity, selection bias, or reverse causality. This methodological approach enhances the credibility of our findings and underscores the significant role of GI registration in improving the economic well-being of workers in GI gardens.

Unconditional Quantile Regression (UQR) Model

The Unconditional Quantile Regression (UQR)model allows us to estimate the heterogeneous effect of GI employment on welfare, specifically on workers' consumption expenditure. According to Ma et al. (2020), “in its simplest form, a UQR model can be estimated as a simple OLS regression on a transformed dependent variable using the recentered influence function (RIF)” (Firpo et al., 2009; Mishra et al., 2015). The following equations illustrate this approach:

$$RIF(Y_i;\ Q_\tau, F_Y) = \omega_i + GI_i + \varphi_i X_i + \varrho_i, \tag{6}$$

Here, Q denotes the τth quantile of the outcome cumulative distribution A_Y; GI_i and Xi have the same specifications as defined in Equation (1); ω_i and φ_i are parameters to be estimated; and ϱ_i is an error term. The RIF in Equation (4) is defined as:

$$RIF(Y_i;\ Q_\tau, F_Y) = Q_\tau + \ \tau \ - \ I(Y_i \leq Q_\tau)\ / f_Y(Q_\tau) \tag{7}$$

where the probability distribution function of variable Y_i is f_Y, and I (·) is the indicator function.

To estimate Equation (6), it is important to address potential endogeneity associated with the GI variable for consistent estimations. Since the treatment of GI is not random in practice, we treat the GI variable as endogenous in the UQR model estimation.

In our study, we employ the IVQR model to account for endogenous covariates using the Inverse Quantile Regression (IQR) estimator following Chernozhukov and Hansen (2006) and the Smoothed Estimating Equations (SEE) estimator following Kaplan and Sun (2017).

This approach allows us to estimate the impact of GI employment across different points of the consumption distribution, providing a comprehensive understanding of its heterogeneous effects on worker welfare. By addressing endogeneity through

IVQR, we ensure that our estimations are robust and reliable, providing deeper insights into the role of GI registration in enhancing workers' economic well-being.

7.3 Empirical Results and Discussion

7.3.1 Baseline Results: Role of GI on Consumption Expenditure

Table 7.3 presents the Ordinary Least Squares (OLS) regression estimates. Column 1 reports the results for all workers, pooling data from both GI and NGI gardens. Columns 2 and 3 provide separate estimations for GI and NGI workers, respectively. Our findings highlight the significant role of GI registration in influencing consumption expenditure. Specifically, the coefficient for GI is positive and statistically significant, indicating that, all else being equal, GI workers exhibit higher consumption expenditure compared to their NGI counterparts. On average, GI workers demonstrate a 40% higher consumption expenditure than NGI workers. These results align with studies suggesting that GI adoption contributes to household well-being (Jena and Grote, 2012; Jena et al., 2015; Belletti and Marescotti, 2021).

Among individual and household characteristics, family size, having employed household members, and distance to the city significantly influence consumption expenditure. A positive coefficient for family size indicates that larger families have higher consumption expenditure, consistent with existing evidence (Dornbusch et al., 2004; Kiran and Dhawan, 2015). This may be due to increased needs and expenses associated with larger households. Additionally, the presence of employed household members is positively associated with consumption expenditure, aligning with economic theory that additional income leads to increased spending (Hensen, 1947; Friedman, 1957; Tai-Yuen, 2016). Conversely, distance to the city negatively influences consumption expenditure, indicating that households farther from urban centers spend less on consumption due to reduced access to markets and higher transportation costs (Casaburi et al., 2013; Melchoir, 2016; Cai et al., 2022).

To verify the consistency of these findings, we perform OLS estimations separately for GI and NGI workers, as shown in Columns 2 and 3 of Table 7.3. Reassuringly, these disaggregated estimates confirm the findings from the pooled regressions. The relationship between selected variables and consumption expenditure remains consistent across both groups, though the magnitude of influence varies. Despite these robust findings, potential endogeneity issues must be addressed. OLS alone may not suffice to infer causality due to possible biases. Hence, we employ Instrumental Variable Treatment Regression (IVTR) model to provide more reliable estimates of the causal impact of GI registration on consumption expenditure.

Table 7.3: GI and Consumption: OLS and IVTR estimates

Independent Variables	Dependent Variable: Consumption (log)			
	All Workers	GI Workers	NGI Workers	IVTR
	(1)	(2)	(3)	(4)
GI	0.4060***	-	-	0.3139**
	(0.0983)			(0.1053)
Female	-0.0212	0.0291	-0.0872	-0.0870
	(0.0445)	(0.0571)	(0.0682)	(0.0647)
Age (log)	-0.0439	-0.2232	0.0105	0.0081
	(0.127)	(0.1868)	(0.1866)	(0.1771)
Social group	0.0210	0.0294	0.0138	0.0135
	(0.0176)	(0.0215)	(0.029)	(0.0275)
Education	0.0093	0.0118	0.0071	0.0071
	(0.0068)	(0.0087)	(0.0103)	(0.0097)
Index of Asset	0.0398	0.0120	0.0938	0.0943*
	(0.0362)	(0.0453)	(0.0571)	(0.0542)
Family size	-0.0969***	-0.1521***	-0.0725***	-0.0724***
	(0.0184)	(0.0274)	(.0246)	(0.0233)
Employed household member	0.2355***	0.3053***	0.1611**	0.1615**
	(0.0464)	(0.0583)	(0.0721)	(0.0684)
Distance to city (log)	-0.1259**	0.1318	-0.2669***	-0.2731***
	(0.0613)	(0.0951)	(0.0798)	(0.0763)
Constant	8.0249***	8.2270***	8.1781***	8.2016***
	(0.5236)	(0.7603)	(0.7682)	(0.7297)
Number of Observations	177	83	94	177
R-squared	0.37511	0.42492	0.24488	0.4450

Notes: Standard errors are reported in parentheses; *** p<0.01, **p<0.05, *p<0.10
Source: Own estimates.

7.3.2 IVTR Estimation

Our IVTR estimation (Table 7.3, column 4) reaffirms the positive and significant impact of GI registration on the consumption expenditure of GI workers. Specifically, the consumption expenditure of GI workers is, on average, 31 percent higher than that of NGI workers. This result corroborates our OLS estimation (Table 7.3, column 1), emphasizing that GI workers indeed allocate more towards consumption compared to their counterparts. Consequently, the GI intervention emerges as a catalyst for boosting consumption expenditure, in line with the findings of Jena and Grote (2012), Ngokkuen and Grote (2012), and Török et al (2020).

Moreover, the control variables exhibit a consistent pattern of influence in our IVTR estimation, mirroring the baseline OLS estimates. Notably, the purchase of durable assets and diversified income sources continue to positively influence consumption. This indicates that higher family income from multiple sources enables workers to spend more on both durable goods and consumables. Surprisingly, the estimation shows that greater distance from the garden residence to the main city reduces consumption expenditure, suggesting that remoteness limits access to goods and services, leading to lower overall consumption expenditure.

7.3.3 Impact of GI across Consumption Distribution: IVQR Results

To gain further insights into how the difference in consumption between GI and NGI workers evolves across the consumption distribution, we evaluate the differences at every decile of the consumption distribution. This approach allows us to estimate the contribution of each covariate in explaining consumption differences at different consumption quantiles. Our IVQR model helps us understand the heterogeneous GI effect across the consumption distribution (Table 7.4 and Figure A7.1).

The GI coefficient, representing the treatment effect, ranges from 30% to 50% across the quantiles after controlling for other key factors influencing consumption. The positive and significant GI coefficients indicate that GI workers' consumption expenditure is higher than that of NGI workers at every quantile. The magnitude of the GI effect diminishes across the quantiles, being larger at the lower quantiles and decreasing as we move up the distribution, from 50% to 30%. This suggests that GI as a policy benefits the poorest workers more than those at the higher end of the consumption distribution (Figure A7.1).

The higher GI effect at the lower tail suggests that the consumption of the poorest workers is more sensitive to GI treatment, thereby reducing income risks[28] and positively impacting their consumption spending. This finding aligns with our earlier analysis of the wage gap favoring GI workers at the lower tail of the wage distribution. The positive GI effect on the lower wage distribution contributes to the higher GI effect on the lower tail of the consumption distribution. Our empirical evidence suggests that the poorest workers benefit more from GI treatment relative to their counterparts, emphasizing the policy perspective that GI is a welfare-enhancing tool for poor workers producing GI products.

[28] Workers' over-dependence on a single income source is likely to result in welfare loss (Xu, 2017). However, GI also provides other economic opportunities, such as rural tourism, enabling poor workers to diversify their income sources and thereby reduce income risks (Lecoent et al., 2010; Dogan and Gokovali, 2012).

Table 7.4: Effect of GI on Consumption by Selected Percentiles

Independent Variables	Dependent variable: Consumption expenditure (log)								
	q10	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
GI	0.5072***	0.4730***	0.4454***	0.4253***	0.4077***	0.3845***	0.3582***	0.3363**	0.3048*
	(0.1271)	(0.1084)	(0.1012)	(0.1018)	(0.1063)	(0.1169)	(0.1341)	(0.1511)	(0.1793)
Female	0.0179	0.0030	-0.0091	-0.0179	-0.0256	-0.0358	-0.0473	-0.0569	-0.0707
	(0.0718)	(0.0620)	(0.0560)	(0.0531)	(0.0518)	(0.0520)	(0.0547)	(0.0588)	(0.0671)
Age (log)	-0.0449	-0.0402	-0.0364	-0.0337	-0.0312	-0.0280	-0.0244	-0.0214	-0.0171
	(0.1546)	(0.1307)	(0.1220)	(0.1231)	(0.1291)	(0.1433)	(0.1657)	(0.1878)	(0.2231)
Social group	0.0149	0.0169	0.0186	0.0198	0.0209	0.0222	0.0238	0.0251	0.0270
	(0.0207)	(0.0179)	(0.0167)	(0.0165)	(0.0170)	(0.0183)	(0.0206)	(0.0229)	(0.0268)
Education	-0.0011	0.0010	0.0027	0.0039	0.0050	0.0064	0.0081	0.0094	0.0113
	(0.0122)	(0.0101)	(0.0088)	(0.0082)	(0.0079)	(0.0079)	(0.0085)	(0.0094)	(0.0111)
Index of Asset	0.0232	0.0284	0.0327	0.0358	0.0385	0.0420	0.0461	0.0495	0.0543
	(0.0611)	(0.0510)	(0.0449)	(0.0422)	(0.0413)	(0.0424)	(0.0463)	(0.0514)	(0.0608)
Family size	-0.1517***	-0.1388***	-0.1284***	-0.1209***	-0.1142***	-0.1055***	-0.0956***	-0.0874***	-0.0755***
	(0.0349)	(0.0298)	(0.0263)	(0.0245)	(0.0235)	(0.0231)	(0.0240)	(0.0256)	(0.0297)
Employed household member	0.2033**	0.2151***	0.2247***	0.2316***	0.2377***	0.2457***	0.2548***	0.2624***	0.2732***
	(0.0649)	(0.0551)	(0.0494)	(0.0468)	(0.0460)	(0.0469)	(0.0507)	(0.0556)	(0.0648)
Distance to city (log)	-0.1814**	-0.1630**	-0.1481**	-0.1373**	-0.1278**	-0.1153*	-0.1011	-0.0893	-0.0723
	(0.0911)	(0.0765)	(0.0683)	(0.0652)	(0.0649)	(0.0676)	(0.0749)	(0.0833)	(0.0986)
Constant	8.1596***	8.1268***	8.1003***	8.0810***	8.0642***	8.0419***	8.0167***	7.9957***	7.9655***
	(0.6825)	(0.5672)	(0.5145)	(0.5064)	(0.5218)	(0.5710)	(0.6573)	(0.7466)	(0.8918)

Note: Standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10
Source: Own estimates.

7.3.4 Robustness Check

As part of the robustness check, we conducted the IVTR estimation on a sub-sample consisting only of GI and NGI workers whose principal income source is tea wage income. The sub-sample analysis yielded consistent results with our main estimation, demonstrating that the positive impact of GI on consumption expenditure remains stable across different sample sizes. Table A7.1 presents the results of this robustness check.

7.4 Conclusion

In this Chapter, we examined the average and distributional effects of GI across consumption deciles using IVTR and IVQR models, respectively, to address the endogeneity associated with GI adoption. Our findings highlighted the positive impacts of GI on workers' welfare. On average, GI workers exhibited approximately 31% higher consumption expenditure compared to their counterparts. Moreover, the GI effect was more pronounced for the poorest workers in the lower consumption quantiles, highlighting the greater benefit of GI for workers with lower consumption spending.

Our results support the emerging discourse that GI protection enhances welfare, particularly benefitting poor workers. This chapter concludes our empirical investigation into the role of GI in the Indian Tea Industry. The subsequent chapter summarizes our findings, discusses the limitations of the study, and provides policy recommendations based on the empirical results.

CHAPTER 8

CONCLUSION

Geographical indications (GIs) are increasingly recognized as a valuable legal tool that links products to their place of origin, people, culture, and history. This recognition is driven by a growing consumer preference for authentic, safe, quality, and healthy food products. Like other forms of intellectual property rights, GIs grant exclusive rights to firms, empowering them to outperform their counterparts. These positive effects are crucial for industries based in rural areas, employing rural communities. Therefore, the Indian tea industry presents an ideal case for investigating the effects of GIs. Existing studies have shown that GIs can enhance firm performance by boosting prices, sales revenue, trade and export, investment, income, and employment. In addition, GIs are seen to promote territorial development through rural entrepreneurship, employment, tourism, and handicrafts. However, much of this evidence comes from European nations, with limited empirical scrutiny of GI effects in Asia, including India. Hence, insights from existing studies may not fully capture the impact of GIs on firm performance in India, nor offer comprehensive policy suggestions.

This study aims to fill this gap in the literature by focusing on the effects of GIs on tea manufacturing firms in India. We began by discussing various data sources used and the data cleaning process to arrive at the final dataset. Recognising the shortcomings of secondary data, we also conducted a field survey to collect information from garden workers, permitting us to examine the effects at the worker level. Our multi-level approach provides a comprehensive understanding of the GI effect. Next, we reviewed studies on the impacts of GIs on firm performance and compared the performance of the Indian tea industry with the food and beverages (F&B) and manufacturing sectors using firm-level data. Subsequently, we investigated the impact of GIs on the performance of tea manufacturing firms and examined wage differentials between GI and NGI firms, along with factors influencing wage inequality. Further, we probed the role of GIs in improving garden employment and analysed the welfare dimensions of GI adoption.

For secondary data, we relied on firm-level data from the Annual Survey of Industries (ASI) and garden-level data from a survey conducted by the Labour Department, Government of West Bengal. To address gaps in secondary data, we supplemented our study with primary data collected from workers. To fulfil our objectives, we employed various econometric methods, including Propensity Score Matching-Difference-in-Differences (PSM-DID), Oaxaca-Blinder and RIF-decomposition methods, Endogenous Treatment Regression (ETR), Exogenous Switching Regression (ESR), Instrumental Variable Treatment Regression (IVTR), and Unconditional Quantile Regression (UQR). Robustness checks were also conducted to ensure the reliability of our results.

KEY FINDINGS

Lacklustre performance of the Tea industry

Our analysis revealed a noticeable but declining presence of the Tea industry within the Indian F&B and Manufacturing sectors. This trend is worrying, given the industry's significant role in employment and the rural economy. The main reason for this underperformance is the faster growth of the broader Indian F&B and manufacturing sectors. We observed substantial variations in the magnitude of tea industry across different firm characteristics, with a higher presence of rural, privately owned, and older firms. From 2000 to 2009, we also noted a growing share of Geographical Indication (GI) certified firms within the tea industry. These GI firms demonstrate improvements in capital investment and wages compared to non-GI firms, highlighting the economic benefits of GI certification.

GIs propel firm performance

Our firm-level analysis using ASI data suggests that GIs positively influence investment and wages in the tea industry. GI certification significantly enhances firm performance, allowing firms to increase investment by 3% and wages by 13%. This aligns with the view that GI registration attracts investment and improves worker welfare. However, employment and output were not significantly affected by GI treatment. This suggests that producers may focus on quality improvement over increased output, or that rising capital use may substitute labor. Further, the presence of counterfeit GI products could impact output and employment. Robustness tests confirm the critical role of GI in boosting investment and highlight the contentious issue of wages in the tea industry. These findings emphasize the significant role of GIs in improving firm performance and worker compensation, offering a positive outlook for the industry.

GIs reward poor workers

Our analysis of wage differences between GI and non-GI tea manufacturing firms using Oaxaca and RIF-Oaxaca decomposition methods reveals significant insights. The wage gap between these firms is unevenly distributed across the wage spectrum, with GI firms paying more at the lower deciles and NGI firms paying more at the higher deciles. This suggests that GI certification benefits lower-wage workers more significantly, aligning with the goal of GIs to support poorer workers. The wage gap is highest at the 90^{th} quantile and lowest at the 30^{th} quantile, increasing from 18 percent at the 50^{th} decile to 40 percent at the 90^{th} decile due to structural effects, while composition effects narrow the gap by 9 to 15 percent. Key factors such as urbanization and capital intensity help reduce the gap through composition effects, whereas literacy, bank branch density, and capital intensity expand it through structural effects. Our findings highlight the importance of addressing both structural and composition effects to reduce wage inequality.

GIs fuel employment surge

Plantation employment is crucial for the rural economy, especially in India's tea-growing areas like Darjeeling, West Bengal. Our investigation into the employment implications of GI adoption in the Indian tea industry uncovers important findings. We found that GI gardens consistently hire more workers than non-GI gardens, with an average increase of one additional worker per two hectares. Without GI registration, GI gardens would have seen lower employment growth, showing missed opportunities for non-GI gardens that could have achieved higher growth with GI treatment. Specifically, GI gardens show an employment growth of about 3.34 employees per hectare, compared to 3.16 employees in NGI gardens, and without GI adoption, GI gardens' growth would have been only 2.85 employees per hectare. Further analysis supports these findings, showing a positive GI effect across various garden types. The observed heterogeneity in effects suggests that inherent garden characteristics also play a crucial role in explaining employment disparities. Overall, these results show that adopting GI helps create more jobs in the tea industry, proving that GI policies effectively boost rural employment and support economic growth in tea-producing regions.

GIs empower welfare

Tea gardens not only provide employment but also essential welfare benefits to workers. Advocates argue that GIs improve these welfare aspects. Our investigation sheds light on how GI adoption impacts worker welfare. We find that GI registration significantly boosts workers' consumption expenditure. Specifically, GI workers demonstrate a 40% higher consumption expenditure than non-GI workers, aligning with studies suggesting that GI adoption contributes to household well-being. Our robustness tests, which address concerns about potential biases, confirm that GI workers' consumption expenditure remains consistently higher than that of non-GI workers. Moreover, our analysis reveals a substantial positive impact of GI across different consumption levels, ranging from 30% to 50%. This effect is most pronounced among the poorest workers, indicating that GI adoption reduces income risks and enhances welfare among vulnerable groups. These findings underscore the role of GIs in improving living standards by providing economic benefits for workers in tea-producing regions.

POLICY IMPLICATIONS

Our study highlights the critical role of GI registration in shaping firm performance, highlighting its potential to enhance employment in tea gardens and improve worker welfare. Based on these findings, our policy recommendations aim to maximise the impact of GI registration and enhance its effectiveness.

First, our research underscores the critical role of GI registration in driving firm investment and improving wages, particularly for quality-focused GI-certified firms. These firms benefit from enhanced investment opportunities, which correlate positively with product quality and financial returns. To further bolster these benefits, timely financial support from institutions such as the Tea Board of India and NABARD (National Bank for Agriculture and Rural Development) through quality enhancement schemes is crucial. Such support can effectively meet investment needs and empower firms to compete more vigorously in the market, thereby enabling better compensation for workers.

Second, our study highlights a wage disparity between GI and NGI firms influenced by both regional and firm-specific factors. Challenges like limited urbanization and lower literacy rates deter GI firms from offering competitive wages. To address this, effective urban development plans and improved access to bank credit are essential. India’s initiatives to augment rural physical and digital infrastructure are central to fostering economic growth in rural areas and enhancing overall living standards. Moreover, targeted policies promoting technology adoption and skills development can help bridge the wage gap by enhancing productivity and competitiveness across the tea industry. These efforts are crucial for ensuring equitable economic development and improving the livelihoods of workers in tea-producing regions.

Third, our findings underscore the employment benefits of GI adoption in tea gardens, where GI-registered gardens employ more workers per hectare compared to non-GI gardens. This highlights the employment-generating potential of prioritizing quality over volume in tea production. Encouraging tea gardens to adopt GI registration not only enhances productivity but also supports higher wages and strengthens market competitiveness. Therefore, promoting GI adoption is crucial for fostering rural employment, enhancing worker welfare, and ensuring sustainable economic growth in tea-producing regions. Additionally, implementing supportive policies such as financial incentives for quality enhancement and infrastructure development can further amplify these positive impacts.

Fourthly, GI registration significantly enhances labour welfare in the tea industry. Our findings indicate that GI adoption promotes worker well-being, evident from their higher consumption levels compared to non-GI workers. This improvement is crucial given the challenges tea garden workers face, including low wages contributing to inadequate consumption and welfare facilities. Enhancing worker well-being through GI adoption is key to the ongoing discussions to improve conditions for tea workers. Policymakers and authorities should prioritize initiatives promoting GI adoption, facilitating access to financial incentives and improving social welfare infrastructure. These efforts will support sustainable improvements in living standards and address labour welfare issues effectively.

Fifth, the success of GI legislation hinges on effective enforcement and monitoring. Strengthening enforcement measures to prevent unauthorized use of GI labels is crucial for achieving desired outcomes. Industry representatives, tea workers' unions, and parliamentary committees argue for curbing the supply and sale of teas from neighbouring countries falsely marketed as Darjeeling tea. Beyond registration, effective marketing strategies, quality communication, institutional support, and rigorous enforcement by regulatory bodies are essential to safeguarding GI integrity and realizing expected benefits.

By implementing these policy recommendations, India can leverage GI adoption for some of its renowned tea brands to enhance market competitiveness, attract investment, generate employment, offer higher remuneration, promote sustainable development in tea-producing regions, and preserve the cultural heritage associated with the iconic beverage.

LIMITATIONS AND SCOPE OF THE STUDY

Our study focuses exclusively on assessing the impact of GI registration in the Indian tea industry. While this provides valuable insights, it restricts the broader applicability of our findings. A more comprehensive approach would involve examining GI effects across various product categories and industries. In addition, our analysis is constrained by the availability of firm-level data with district-level identifiers spanning from 1999-2000 to 2008-2009. The short duration of data collection restricts our ability to observe long-term GI effects, highlighting the need for datasets for longer duration to capture comprehensive trends. Moreover, the absence of baseline data poses challenges in conducting thorough pre- and post-registration comparisons.

Moreover, GI registration alone does not guarantee automatic benefits; it necessitates robust institutional support, stringent quality control measures, effective marketing strategies, producer cooperation, consumer awareness campaigns, international protection, and collaboration from relevant stakeholders. This complex interplay makes it methodologically challenging to isolate and quantify the true impact of GI.

Another significant limitation pertains to constructing a suitable control group of equally reputable tea firms without GI registration. The performance of tea firms is influenced by a multitude of factors, many of which are location-specific and regional in nature. This complicates the task of identifying statistically comparable control groups necessary for precise impact measurement.

It is crucial for future studies to address these limitations to enrich the empirical literature on GI effects. Overcoming these challenges will facilitate deeper insights into the potential benefits and challenges associated with GI registration, contributing to more informed policy decisions and industry strategies.

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APPENDICES

Table A5.1: Decomposition of the wage gap by percentiles: RIF-Oaxaca detailed decomposition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Overall									
Mean NGI wage	9.4819***	9.5865***	9.6703***	9.7475***	9.8325***	9.9448***	10.0518***	10.1817***	10.3882***
per worker (N)	(0.0261)	(0.0389)	(0.0503)	(0.0637)	(0.0771)	(0.0861)	(0.0807)	(0.0809)	(0.0874)
Mean GI wage per	9.6188***	9.6981***	9.7564***	9.8065***	9.8587***	9.9063***	9.9676***	10.0455***	10.1408***
worker (G)	(0.0053)	(0.0062)	(0.0072)	(0.0087)	(0.0105)	(0.0125)	(0.0172)	(0.0263)	(0.0492)
GI gap in wage	-0.1369***	-0.1116***	-0.0860*	-0.0589	-0.0262	0.0384	0.0841	0.1362	0.1474**
(N-G)	(0.0266)	(0.0394)	(0.0509)	(0.0643)	(0.0778)	(0.0870)	(0.0825)	(0.0851)	(0.1004)
Reweighted decomposition									
Counterfactual (C)	9.5332***	9.6788***	9.8080***	9.9249***	10.0396***	10.1324***	10.2411***	10.3398***	10.5359***
	(0.0316)	(0.0549)	(0.0761)	(0.0846)	(0.0701)	(0.0626)	(0.0522)	(0.0509)	(0.0601)
Total composition	-0.0512	-0.0923*	-0.1376*	-0.1774**	-0.2071**	-.01876**	-0.1893***	-0.1581***	-0.1477**
effect (N-C)	(0.0410)	(0.0564)	(0.0749)	(0.0885)	(0.0865)	(0.0786)	(0.06472)	(0.0534)	(0.0625)
Total Structural	-0.0856**	-0.0192	0.0516	0.1184	0.1808**	0.2260***	0.2735***	0.2943***	0.3951***
effect (C-G)	(0.0353)	(0.0587)	(0.0795)	(0.0871)	(0.0722)	(0.0652)	(0.0558)	(0.0585)	(0.0792)
RIF aggregate decomposition									
Pure composition	-0.02741	-0.0565**	-0.0814***	-0.1204***	-0.1647***	-0.2123***	-0.2180***	-0.2184***	-0.2225***
effect	(0.0216)	(0.0275)	(0.0316)	(0.0348)	(0.0375)	(0.0362)	(-.0392)	(0.0407)	(0.0615)
Specification error	-0.0238	-0.0357	-0.0562	-0.0569	-0.0424	0.0247	0.0287	0.0603	0.0748
	(0.0312)	(0.0390)	(0.0554)	(0.0639)	(0.0584)	(0.0671)	(0.0715)	(0.0678)	(0.0962)
Pure structural	-0.0959***	-0.0367	0.0238	0.0832***	0.1513***	0.1996***	0.2506***	0.2720***	0.3693***
effect	(0.0212)	(0.0273)	(0.0301)	(0.0267)	(0.0241)	(0.0303)	(0.0344)	(0.0359)	(0.0656)
Reweighting error	0.0102	0.0175	0.0277	0.0351	0.0295	0.0264	0 .0228	0.0223	0.0257
	(0.0309)	(0.0540)	(0.0754)	(0.0841)	(0.0701)	(0.0638)	(0.0542)	(0.0510)	(0.0613)
Pure composition effect									
Size	-0.0091	-0.0112	-0.0175	-0.0236	-0.0187	-0.0198	-0.0190*	-0.0149*	-0.0141
	(0.0167)	(0.0201)	(0.0225)	(0.0202)	(0.0155)	(0.0135)	(0.0097)	(0.0085)	0.0124)
Age	0.0058	0.0041	0.0028	-0.0007	0.0002	0.0028	0.0013	0.0052	0.0154
	(0.0101)	(0.0093)	(0.0111)	(0.0105)	(0.0100)	(0.0106)	(0.0072)	(0.0060)	(0.0121)
Capital intensity	-0.0043	-0.0042*	-0.0042*	-0.0048*	-0.0048*	-0.0068*	-0.0056*	-0.0053*	-0.0076
(log)	(0.0027)	(0.0025)	(0.0023)	(0.0025)	(0.0027)	(0.0036)	(0.0033)	(0.0032)	(0.0052)
Bank branch	0.0065	0.0114	0.0179	0.0188	0.0073	-0.0229	-0.0394	-0.0345	-0.0494

density	(0.0245)	(0.0311)	(0.0373)	(0.0417)	(0.0468)	(0.0494)	(0.0458)	(0.0493)	(0.0813)
Literacy rate	-0.0016	-0.0151	-0.0234	-0.0361	-0.0550	-0.0565	-0.0368	-0.0263	-0.0151
	(0.0198)	(0.0297)	(0.0378)	(0.0447)	(0.0443)	(0.0421)	(0.0353)	(0.0305)	(0.0377)
Share of SC	0.0043	0.0010	0.0011	0.0021	0.0051	0.0097	0 .0160	0.0243	0.0301
population	(0.0145)	(0.0153)	(0.0161)	(0.0169)	(0.0172)	(0.0160)	(0.0145)	(0.0187)	(0.0273)
Urbanisation	-0.0290	-0.0426	-0.0582	-0.0760	-0.0987*	-.1189**	-.1345***	-.1668***	-0.1818**
	(0.0423)	(0.0462)	(0.0482)	(0.0497)	(0.0523)	(.0523)	(.0450)	(.0521)	(0.0804)
Pure structural effect									
Size	0.1131**	-0.0308	-0.0424	-0.0139	-0.0127	-0.0169	-0.0325**	-0.0002	-0.0704***
	(0.0498)	(0.0489)	(0.0362)	(0.0307)	(0.0213)	(0.0170)	(0.0159)	(0.0139)	(0.0244)
Age	-0.0713***	0.0364	0.0596*	-0.0264	-0.0084	-0.0173	0.0346	-0.0705*	-0.1792***
	(0.0273)	(0.0281)	(0.0313)	(0.0382)	(0.0321)	(0.0312)	(0.0292)	(0.0391)	(0.0462)
Capital intensity	-0.2140	0.0638	0.1073	0.4258***	0.2960**	0.2776	0.3779	0.2523	-0.6326
(log)	(0.1567)	(0.0988)	(0.1302)	(0.1487)	(0.1452)	(0.2451)	(0.2489)	(0.3838)	(0.8803)
Bank branch	1.0135**	0.8524**	0.3517	0.7338	0.7817	0.4462	0.7318	0.0874	-1.1017
density	(0.4394)	(0.3981)	(0.3496)	(0.4900)	(0.7124)	(0.4158)	(0.6373)	(0.3180)	(0.7853)
Literacy rate	-0.2206	0.2080	0.9739**	1.6408***	1.9875***	0.6269	0 .2725	1.1373***	-2.1545***
	(0.6068)	(0.38910)	(0.4955)	(0.5771)	(0.6278)	(0.5176)	(0.5194)	(0.4213)	(0.2348)
Share of SC	-3.4362***	-2.6619***	-1.7563***	-3.8184***	-4.8625***	-2.9942***	-3.0184***	-3.3508***	2.5256
population	(0.1470)	(.3961)	(0.1383)	(0.3128)	(0.7142)	(0.1893)	(0.6378)	(0.0603)	(2.0821)
Urbanisation	-0.2072	0.0358	0.1322	-0.1932	-0.3823*	0.1671	0 .5073**	0.0664	2.0222***
	(0.2274)	(.1323)	(0.1826)	(0.2153)	(0.2275)	(0.2116)	(0.2146)	(0.2052)	(0.2482)
Intercept	2.9269***	1.4592***	0.1975	1.3346***	2.3520***	1.7102***	1.3774**	2.1500***	-0.0399
	(0.3005)	(0.3412)	(0.2794)	(0.3513)	0(.5473)	(0.3524)	(0.5624)	(0.3454)	(0.6208)
No. of observation	4440	4440	4440	4440	4440	4440	4440	4440	4440

Note: The dependent variable is the estimated RIF at the respective decile of the log wages per worker. The wage gap is the difference between the log wage per worker of NGI firms and GI firms. Sampling weights are used in estimation. In parentheses are standard errors robust to heteroskedasticity and clustered residuals within districts. The reweighting factors are estimated using a logit model. ***, **, and * denote significance at the 1,5, and 10 percent levels, respectively. See Table 5.1 for details of the variables included.

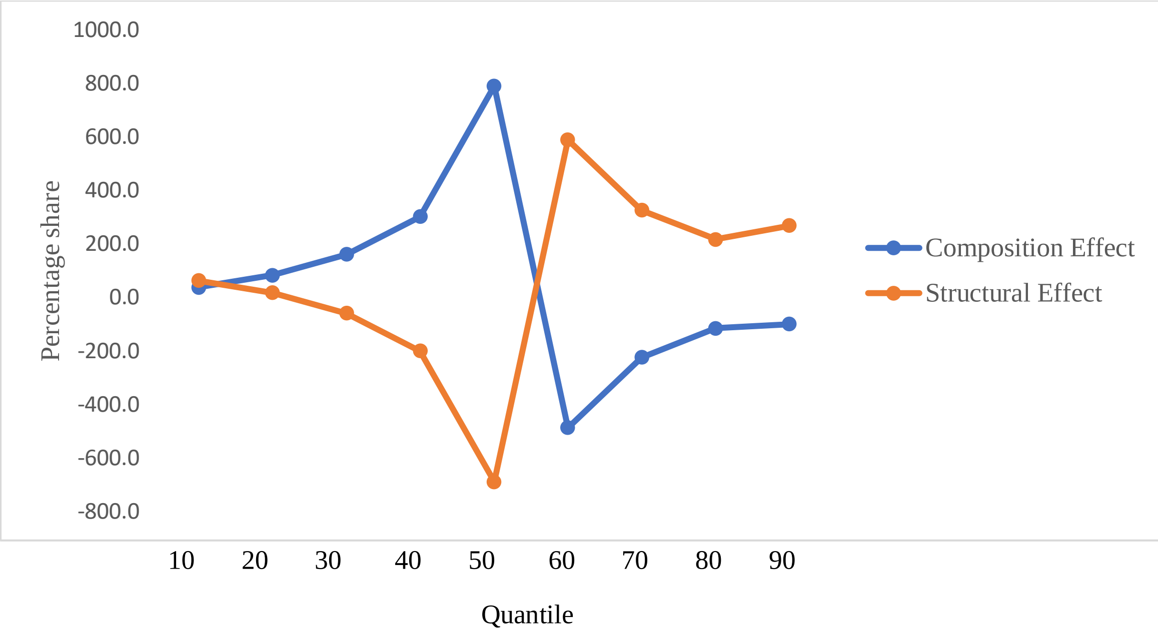
Source: Own estimates.

Table A7.1: GI and Consumption: IVTR estimates

Independent Variables	IVTR Dependent variable: Consumption per capita (log)
GI	0.3947*** (0.0924)
Female	-0.1499 (0.0603)
Age (log)	-0.2358 (0.1809)
Social group	-0.0163 (0.0253)
Education	-0.0185 (0.0103)
Index of Asset	0.0645 (0.0479)
Family size	-0.1244*** (0.0223)
Employed household member	0.1086 (0.0568)
Distance to city (log)	-0.2284* (0.0664)
Constant	9.4147*** (0.7366)
No. of observations	152

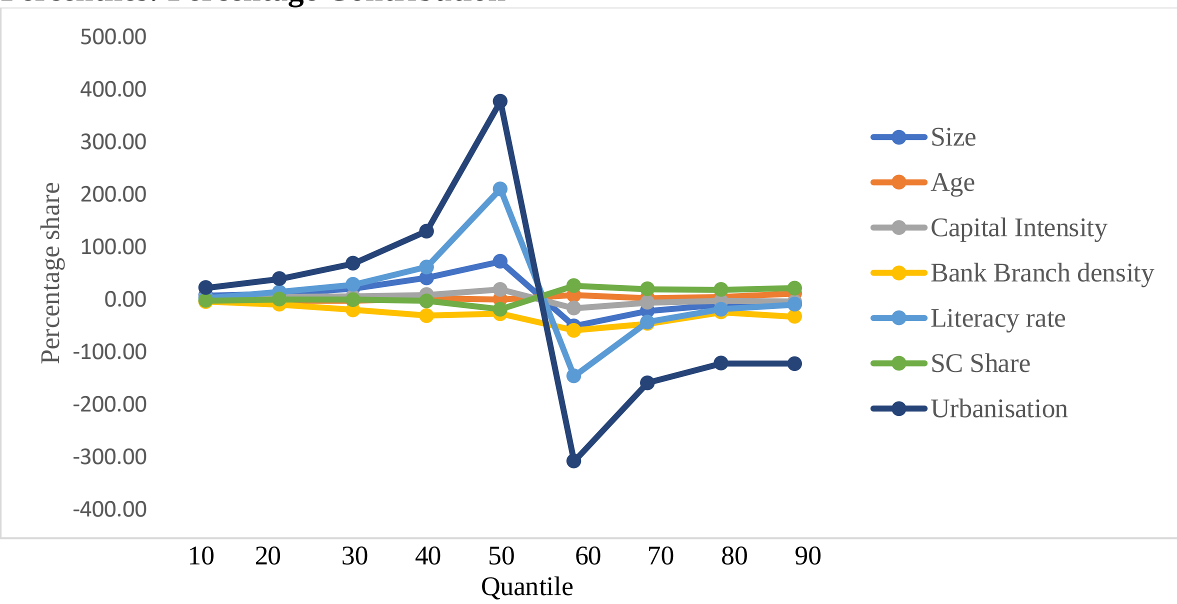
Note: Standard errors are reported in parentheses; *** p<0.01, **p<0.05, *p<0.10
Source: Own estimates.

Figure A5.1: Aggregate RIF-Decomposition by Percentiles: Percentage Contribution



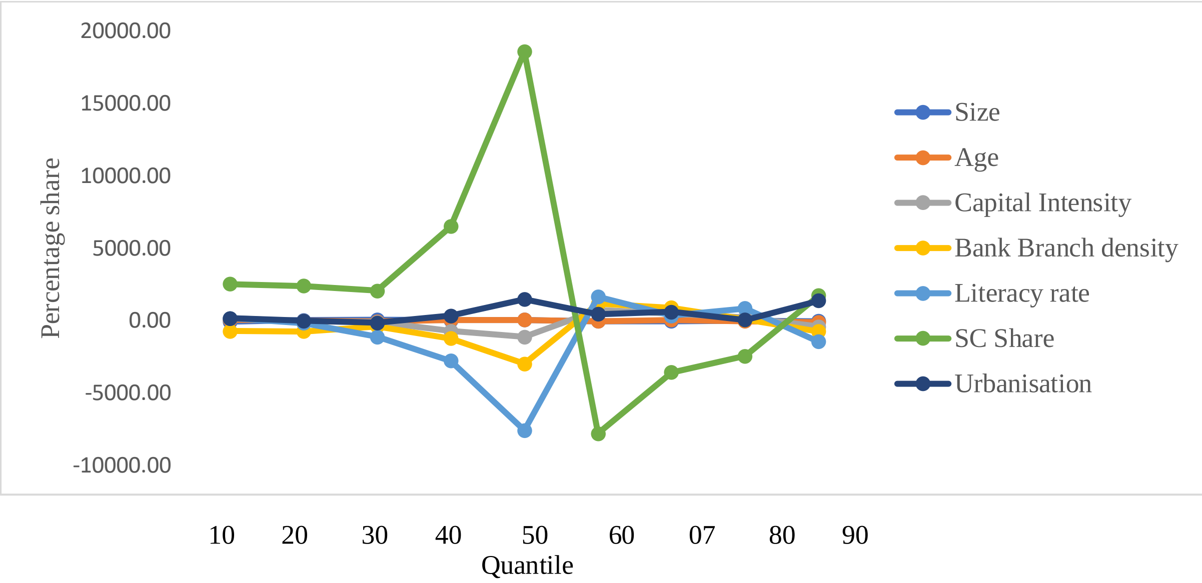
Source: Own estimates.

Figure A5.2: Detailed RIF-Decomposition of the Pure Composition Effects by Percentiles: Percentage Contribution



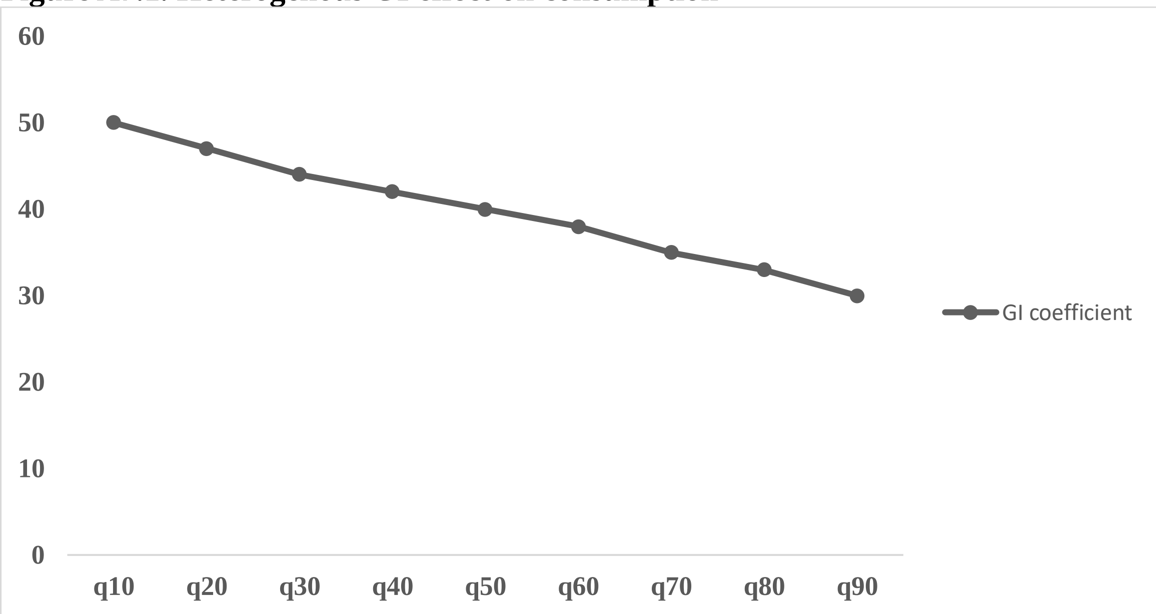
Source: Own estimates.

Figure A5.3: Detailed RIF-Decomposition of Pure Structural Effects by Percentiles: Percentage Contribution



Source: Own estimates.

Figure A7.1. Heterogenous GI effect on consumption



Source: Own estimates.

Questionnaire

1. Name of the garden where you are working:
2. Gender: (A) Female[1] (B) Male[0]
3. Age:
4. Social Background: (A) ST[1] (B) SC[2] (C) OBC[3] (D) Others[0]
5. Education Qualification: No. of years of schooling, If Illiterate[0]
6. Number of years of employment in the garden (or year of employment):

7A. Were you employed before joining this garden? (A) Yes[1] (B) No[0]

7B. If Yes, where & in which Year:

8. Nature of your present Employment: (A) Permanent[1] (B) Temporary[0]
9. Number of working hours?
10. Do you meet the plucking targets? (A) Yes[1] (B) No[0]
11. Your highest Kg of tea leaves plucked?
12. Total number of workers in your garden:
13. Have you been living in the same garden village since birth? (A) Yes[1] (B) No[0]
14. What do you have to say about Darjeeling tea?
15. Do you know about other teas (i.e. non-Darjeeling teas) that are also being sold as Darjeeling tea? (A) Yes[1] (B) No[0]
16. What is the principal source of your family income?

(A) Your Wage[1] B) Your Husband's/Wife's income[2] (C) Others[0] ……(Please mention)

17A. Any other employed family member: (A) Yes[1] (B) No[0]

17B. If Yes, then employed as (A) Daily wage earner[1] (B) Govt. Job[2] (C) Private Job[3] (D)

Self-Employed[4] (E) Others[0]

18. What is your total family monthly income?
19. What is your total monthly family expenditure?
20. Most of your income is spent on:

(A) Food items[1] (B) Children's education[2] (C) Medical[3] (D) Clothing[4] (E) Entertainment[5] (F) Others[0]

21. Do you have a BPL card?

(A) Yes[1] (B) No[0]

22. Whether married or not:

(A) Yes^{1} (B) No^{0}

23. Number of family members (or family size):

24. Wage Payment: (A) Regular^{1} (On time) (B) Irregular^{0} (Due)

25. How often do you buy grocery items?

(A) Once a week^{1} (B) Twice a week^{2} (C) More than twice a week^{3}.

26. Does your regular shopkeeper provide goods on credit to you? (A) Yes^{1} (B) No^{0}

27. Have you purchased a TV set in the last two years? (A) Yes^{1} (B) No^{0}

28. Have you purchased a new mobile phone in the last two years? (A) Yes^{1} (B) No^{0}

29. Bonus Rate (%) last year?

30. Bonus payment: (A) Regular^{1} (on time) (B) Irregular^{0} (Due).

31. Gratuity, Provident Fund (PF) payment: (A) Regular^{1} (on time) (B) Irregular^{0} (Due).

32. What is the existing Garden Ration scale (Kg per person):

Rice: _Kg per Adult Person & _ Kg per Child.

Wheat: _Kg per Adult Person & _ Kg per Child.

Sugar: _Kg per Adult Person & _ Kg per Child.

Kerosene Oil: _Kg per Adult Person & _ Kg per Child.

33. Distribution of Ration by your company is: (A) Regular^{1} (on time) (B) Irregular^{0} (Due).

34. How many workers' Unions are operating in the garden:

35. Are you part of the Union? (A) Yes^{1} (B) No^{0}

36. Does your Union take up your issue/problem with the Management? (A) Yes^{1} (B) No^{0}

37. Apart from the Union, is there a workers' welfare Association? (A) Yes^{1} (B) No^{0}

38. How many permitted days of leave with pay (or wage) do you get?

39. How many permitted days of leave without pay (or wage) do you get?

40. Are there any improvements in the Sick leave and Maternity leave facility than before (say, 20 years)?

(A) Yes^{1} (B) No^{0}

41A. Free medicine provided by your garden? (A) Yes^{1} (B) No^{0}

41B. Was there a free medicine facility, say, 20 years ago? (A) Yes^{1} (B) No^{0}

42A. Is there a doctor in the garden? (A) Yes^{1} (B) No^{0}

42B. Was there a doctor in the garden, say, 20 years ago? (A) Yes^{1} (B) No^{0}

43A. Availability of Ambulance in the garden? (A) Yes^{1} (B) No^{0}

43B. Was there an Ambulance in the garden, say, 20 years ago? (A) Yes^{1} (B) No^{0}

44A. On average, what is your family's medical expense in a year?

44B. For medical expenses incurred by you, do you get any coverage or reimbursement from your company? (A) Yes^{1} (B) No^{0}

45A. Availability of Creche in the garden: (A) Yes^{1} (B) No^{0}

45B. Was there a Creche in the garden, say, 20 years ago: (A) Yes^{1} (B) No^{0}

46A. Have you or your family member taken any loans? (A) Yes^{1} (B) No^{0}

46B. If Yes, what was the amount & purpose of the loan?

46C. Is the loan fully repaid? (A) Yes^{1} (B) No^{0}

46D. Borrowings (loans) are mostly done from? (A) Banks^{1} (B) Moneylenders^{2} (C) Relatives^{3} (D) Friends^{4} (E) Others^{0}

47A. Any employment opportunity other than a garden job? (A) Yes^{1} (B) No^{0}

47B. If Yes, what is the wage rate of such jobs?

(A) More than garden wage^{1} (B) Less than garden wage^{2} (C) Equal to garden wage^{0}

48A. Present Housing Status: (A) Kacha^{0} (B) Pukka^{1}

48B. Housing Status, say, 20 years ago: (A) Kacha^{0} (B) Pukka^{1}

48C. Present Housing construction was funded by the? (A) Garden^{1} (B) Govt. Scheme^{2} (C) Loan^{3} (D) Own savings (Self)^{4}

48D. The construction of your previous House was funded by the? (A) Garden^{1} (B) Govt.

Scheme^{2} (C) Loan^{3} (D) Own savings (Self)^{4}

49A. Your child/children studies/studied in Govt.^{0} or Private school^{1}?

49B. Does your garden support/fund children's education? (A) Yes1 (B) No^{0}

49C. Did your garden support/fund children's education, say, 20 years ago? (A) Yes^{1} (B) No^{0}

50A. Present Drinking water connection is provided by: (A) Garden^{1} (B) Govt. Scheme^{2} (C) Own^{3} (D) No water connection^{0}

50B. Did you have a drinking water connection, say, 20 years ago? (A) Yes^{1} (B) No^{0}

50C. If yes, the connection was provided by: (A) Garden^{1} (B) Govt. scheme^{2} (C) Own^{3}

51A. Toilet facility in the garden: (A) Kacha^{1} (B) Pakka^{2} (C) Open^{0}

51B. Around 20 years ago, the Toilet facility in the garden was: (A) Kacha^{1} (B) Pakka^{2}

(C) Open^{0}

52A. Fringe Benefits (Firewood, Umbrella, Chappal, Blankets, Tea leaves, gumboots, working field tools) provided:

(A) Not at all^{0} (B) Partially^{1} (C) Fully^{2}

52B. Were fringe Benefits (Firewood, Umbrella, Chappal, Blankets, tea leaves, working field tools, etc.) provided, say 20 years ago? (A) Not at all^{0} (B) Partially^{1} (C) Fully^{2}

53. Over the years, the chances of human-animal conflict at work have:

(A) Increased^{1} (B) Decreased^{2} (C) Same^{0}

54A. Number of Training programs provided by the Management during the last 5 years:

(A) 0^{0} (B) 1-2^{1} (C) More than 2^{2}.

54B. Do you remember such training provided before: (A) Yes^{1} (B) No^{0}

55. Any Outside workers (from other gardens) are employed during peak seasons in your garden:

(A) Yes^{1} (B) No^{0}

56A. You find the present Wage: (A) Low^{0} (B) Just enough^{1} (C) High^{2}

56B. If low, then what do you think should be your ideal wage?

(A) Rs 300-400^{1} (B) Rs 400-500^{2} (B) Above Rs 500^{0}

57A. Overtime work: (A) Optional^{1} (B) Compulsory^{0}

57B. Rate of overtime?

57C. On average, how much do you earn by working overtime in a day?

58A. Do you get a Pension after retirement? (A) Yes^{1} (B) No^{0}

58B. When was the Pension scheme introduced in your garden?

58C. What is the current Pension amount for Senior grade and Junior grade workers?

59. Over the years, has the Road connectivity improved from your garden village to the main bazaar? (A) Yes^{1} (B) No^{0} (C) Same as before^{2}

60. Over the years, has the Power/Electricity supply improved in your garden village? (A) Yes^{1} (B) No^{0} (C) Same as before^{2}

61. Have you heard that Darjeeling tea was registered as Geographical Indications in 2004? (A) Yes^{1} (B) No^{0}
62. How do you feel about your job?
63. What changes do you like to see in your job?

64. Given a chance would you like to change your occupation or start your own business?

    (A) Yes^{1} (B) No^{0}

65. Do you have a canteen in your garden?

    (A) Yes^{1} (B) No^{0}

66. Income from agriculture, animal husbandry or allied activities [Non-garden activities]?

    (A) Nil (B) Rs 1000- Rs 5,000 (C) Rs 5,000-Rs 10,000 (D) Rs 10,000-Rs 20,000 (E) Above Rs 20,000.