# UNIVERSITA' DEGLI STUDI DI VERONA

DEPARTMENT OF ECONOMICS

SCHOOL OF LEGAL AND ECONOMIC SCIENCES

DOCTORAL PROGRAM IN ECONOMICS AND MANAGEMENT

(ECONOMICS CURRICULUM)

WITH THE FINANCIAL CONTRIBUTION OF UniCredit.

Cycle: XXXVI

ESSAYS ON FDI AND MONETARY POLICY IN ETHIOPIA.

S.S.D.: SECS-P/02, SECS-P/11

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# Summary

The level of investment in developing countries is short of the potential investment required for sustained growth and development. Access to finance is also limited in these countries. Developing countries spend significant resources to attract FDI to fill the investment gap and consider FDI an integral part of their industrialization strategies for knowledge transfer. However, an increase in FDI is also expected to increase demand for skilled labor and wage inequality. The low level of investment in developing countries is related to limited access to finance due to underdeveloped financial markets and financial repression which moves financial resources away from the private sector to the government. This Ph.D. thesis explores these issues and contains three self-contained broadly pertinent chapters the technology transfer and labor market outcomes of FDI, and monetary policy in Ethiopia. The first two chapters focus on the effect of horizontal foreign direct investment (FDI) on technology transfer to domestic manufacturing firms and the effect of FDI on labor market outcomes. The third chapter is a quasi-experimental evaluation of a policy change on banks' credit supply.

Chapter 1, "The Competition and Technology Transfer Effect of FDI: Evidence from Ethiopia", explores the pure technology effect of FDI on Ethiopian manufacturing firms. The large body of literature on the knowledge transfer effect of FDI in developing countries finds a negative effect. It interprets the result as the dominance of competition - the market stealing-effect of FDI. Yet, the empirical investigation of separating the two possible countervailing effects of FDI is limited due to the lack of data that can be used to measure the product market competition effect of FDI. To separate the competition effect, the study constructs product closeness and product market rivalry measures using

the four-digit ISIC product classification obtained from the Ethiopian Large and Medium Scale Manufacturing Enterprise Survey for the period from 2013 to 2017. We estimate a model of total factor productivity using Two Stage Least Square (2SLS) regression to identify the causal impact of FDI on technology spillover and competition. The choice of instruments is based on economic theory on exchange rate movements and the flow of FDI and production costs. The result from the IV estimation technique indicates sectoral FDI increases technology spillover to domestic firms in sectors where firms compete in related product groups. The technology spillover effect outweighs the negative product market competition effect of FDI, which is prevalent in sectors where competition is in the same product group. The result confirms that horizontal FDI can have a differential impact on knowledge transfer to domestic firms within a sector depending on the product markets in which foreign firms are competing with domestic firms. The economic significance of the spillover is, however, small given the total factor productivity growth of the manufacturing sector over the study period. The result is robust to the change in the definition of FDI, market competition, and productivity measures.

Chapter 2, "Foreign Direct Investment and Wage Inequality in the Ethiopian Manufacturing Industry", examines the effect of FDI on wage inequality. FDI encourages skill-biased technological change (SBTC) which may exacerbate wage inequality by moving labor demand away from the least skilled to highly skilled workers. Much of the empirical literature on this issue to date, however, has been focused either on developed countries, Latin American or Asian countries. However, the institutional labor market characteristics and administrative capacity of these countries are different from African countries like Ethiopia. This chapter estimates the translog cost function to identify the impact of FDI on within-firm wage inequality using the panel of Ethiopian manufacturing firms for the years between 2013 and 2017. The study finds that despite the rise in wage inequality, the industry did not experience SBTC over the period. The two-stage system-GMM estimates of the translog cost function indicate that a 10% increase in a firm's foreign capital increases the share of skilled labor wages by 1.3 percentage points. FDI also increases firms' relative demand for skilled labor, driving the rise in wage inequality in the industry. These findings suggest that while SBTC is underway at the firm level, it has yet to be translated to the industry.

Chapter 3, “Liquidity Shock and Bank Lending: Evidence from a Natural Experiment in Ethiopia", studies the impact of the liquidity shock on credit supply and its implication for the bank leading channel. Recent studies in developing countries that use standard monetary policies have found the transmission of monetary policy to bank lending and the real economy. However, the financial system in developing countries is still characterized by the dominance of banking systems with underdeveloped inter-bank markets, and weak legal systems which limit the effectiveness of the bank lending channel. This paper exploits the April 2011 mandatory regulatory requirement on new bill purchases as a natural experiment and provides evidence of the causal impact on the bank lending channel of liquidity shocks in Ethiopia. The results from an event study design show that banks whose liquidity was affected by the regulation reduced lending, confirming the prevalence of bank lending channels in developing countries. Specifically, for the same firm-cluster borrowing from two groups of banks exposed to a differential liquidity shock, the average loan and loan repayment period from banks that experienced higher liquidity drainage decreased over the study period. In the short event window, the regulation caused banks to engage in credit rationing by providing small-sized loans with higher repayment frequency to a large number of borrowers, thereby increasing the volume of loan supply by big banks. However, in the relatively long period, the volume of loans and the number of loans remained unaffected, while the effect on average loan size and loan repayment frequency persisted.

# Dedication

**This thesis is dedicated to my late Father!**

# Acknowledgments

I thank God, the almighty, for his countless blessings during this journey of my life. This Ph.D. would not have been possible without the support and guidance of many people.

I would like to express my sincere gratitude to my research supervisors, Professor Angelo Zago and Professor Laura Magazzini. It was a great privilege and honor to work under their guidance. Without their scientific advice, constant feedback, and many insightful discussions, this Ph.D. would not have been possible. I appreciate all their contributions to making my Ph.D. experience stimulating. I'm extremely grateful for the continuous support I received in undertaking fellowships at the National Bank of Ethiopia (NBE), Addis Ababa Ethiopia, and the Center for Effective Global Action (CEGA).

I am also grateful to Professor Alessandro Bucciol, who wrote me recommendation letters and contributed greatly to this successful journey starting from the beginning of my PhD studies. I acknowledge the UniCredit and the University of Verona for granting me the scholarship to pursue my Ph.D. studies. I express my gratitude to my professors in the Department of Economics both at the University of Verona and the University of Padova, particularly to the PhD program coordinator, Prof. Roberto Riciutti. I'm also thankful to the supporting staff of the University of Verona, Chiara Bernardi, Giovanni Baietta, Francesca Limberto, Catia Cordioli, Alessandro Marogna, Sara Avigni, and Anna De Salvo, who were very cooperative and kind throughout my stay at the University.

I express my appreciation for the CEGA/EASST program at Northwestern University (GPRL). Special thanks go to my mentors Professor Sean Higgins, Professor Ameet Morjaria, and Katie Dallia. I would like to express my deepest appreciation to the staff at the NBE, specifically to my ex-colleagues, Fikadu Huriso, Vice Governor Monetary

Stability Cluster, Habtamu Workneh, Director for External Economic Analysis and International Relations Directorate and Woyinshet Weyneshet Zeberga, Director for Monetary and Financial Analysis Directorate, Zemzedm Ahmed, A/Director for Domestic Economic Analysis Directorate for their advice, support and friendship during my fellowship.

I am deeply indebted to my wife and friend, Dr. Saba Yifredew, who deserves special recognition. This journey would not have been possible without her help. The companionship, and academic and emotional support we received from each other have been something that words can't express. I would like to express my deepest gratitude to my father-in-law Yifredew Getnet and my Mother-in-law Atsede Woldemariam for the love, support, and encouragement they have given me and my wife in our studies but also for shouldering the responsibility of raising our children, Yonathan and Rediet during our absence. This endeavor would not have been possible without their unreserved support and sacrifices to take care of our kids. I also express my heartfelt thanks to my mothers Alemitu Terekegen, who has been the main driver of my success, and Tanuguet Eshetet, to my sisters Nigist Zeray and Ayal Demile, and my brothers-in-law Daniel Yifredew, Ephrem Yifredew, and Tewodros Yifredew for their support and prayers.

My Special thanks go to my friend Dr.Netanet Mengistu who paved the way for this journey and gave me continuous support throughout my studies. I would like to say thanks to my friends at the University of Verona including Dr.Cherkos Meaza, Dr. Getachew Belete, Dr.Tekabe Legesse, and Tibebe Aragie for their friendship and constant encouragement. My classmates Giovanni Righetti, Darlington Agbonifi, and Earle John Du Plooy also deserve a special mention. Lastly, my deepest appreciation and special thanks go to Dr. Atnafu Gebremeske, Head of the Department of Economics at Addis Ababa University for his support and guidance.

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# Chapter 1

# Competition and technology spillover effect of foreign direct investment: Evidence from Ethiopia.

**Abstract:**

The literature on technology transfer from FDI in developing countries is inconclusive. The negative effect is interpreted as the dominance of the competition effect of FDI. In this paper, we study the impact of FDI on the productivity of domestic firms and disentangle the two counteracting effects of FDI by constructing product closeness and product market competition indicators using disaggregated product level data for Ethiopian manufacturing firms between 2013 and 2017. We constructed instruments and used the IV method to overcome the endogeneity of FDI and competition. The result shows that horizontal FDI has a differential impact on knowledge transfer to domestic firms within a sector depending on the product markets that firms are competing for. Specifically, we find that sectoral FDI increases technology spillover to domestic firms in the market where product market competition is in related product groups. The technology spillover in related product markets also outweighs the negative product market competition effect of FDI, which is prevalent in the market where firms are competing in the same product group.

*Keywords: FDI, Competition, technology spillover, manufacturing sector, Ethiopia*

*JEL Classification: D24 F21 O33*

## 1.1 Introduction

Foreign direct investment (FDI) is believed to contribute to the economic development of developing countries through technology spillover. The empirical evidence of spillover is, however, inconclusive. Most studies in these countries find that FDI has either no impact Bwalya (2006), Javorcik (2004), Mebratie & Bedi (2013) or has a negative spillover effect Aitken & Harrison (1999), Lu et al. (2017), Waldkirch & Ofosu (2010). Some studies also show a positive technology spillover from FDI Liu (2008), Sjöholm (1999). While the absence of technology transfer is attributed to the low absorption capacity of local firms Blalock & Gertler (2009), Lu et al. (2017), the negative spillover effect is often interpreted as the dominance of competition orthe market-stealing effects of FDI Aitken & Harrison (1999), Harrison (1994). Yet, competition is one of the mechanisms through which knowledge can be transferred to domestic firms and does not necessarily lead to market loss and a decline in productivity. Bloom et al. (2013) indicates that each interaction in a product market between competing firms causes a leakage of knowledge that a domestic firm could utilize to compete more effectively with foreign firms. Competition from foreign firms may also force rival domestic firms to upgrade production techniques to remain productive and competitive Blomström & Kokko (1998), Markusen & Venables (1999), Wang & Blomström (1992).

Understanding the technology transfer effect of FDI in domestic firms in developing countries, therefore, requires identifying the market-stealing effect of FDI. This paper identifies the pure intra-industry knowledge transfer effect of FDI in Ethiopia.[1] Previous studies used different measures and approaches to control for the product rivalry effect that FDI may entail. The popular strategy has been to incorporate the Herfindahl Index(HI) (eg., Girma et al. 2009, Liu 2008, Javorcik 2004) and the firm's market share and industry mark-up (eg., Haskel et al. 2007, Keller & Yeaple 2009) as an extra compo-

[1]The focus of this paper is on intra-industry, not between-industry technology transfer which may happen due to customer or supplier relationships. Throughout this paper, we use Technology spillover and knowledge transfer interchangeably.

nent in addition to FDI in a regression equation. Yet, using industry-level concentration as a measure of competition assumes the same level of competition and ignores intra-industry product heterogeneity. Furthermore, it ignores differences between firms within the industry, since industry classifications may be broad such that they include not only competitors but also suppliers and firms not in the same product market. Thus, HI does not necessarily indicate the competitive interactions among firms in the product market. The use of the conventional measures of competition thus complicates the identification of the competition effect of FDI from its technology spillover. Hence, it is not possible to ascribe the dominance of the competition effect to the negative technology spillover from FDI unless a proper measure of competition capturing foreign firms' market stealing effect is employed.

Despite the extensive coverage of knowledge spillover from FDI in developing countries, studies that show the pure knowledge spillover effect of FDI isolating it from the product market rivalry effect are few and far between. There are at least two possible reasons why investigating the pure technology spillover effect of FDI has been difficult. The first is the lack of a proper measure of product market competition that can capture the level of competition among firms in the same product or related product group. Second, even when such a measure is available, the detailed product group information that can be used to construct such a measure is not available for many developing countries.

To overcome these challenges, this paper exploits several features of the Ethiopian Large and Medium Scale Manufacturing Industry(LMSMI) survey dataset. First, the dataset includes the distribution of firm sales activity/revenue across different product groups classified using a four-digit International Standard Industrial Classification(ISIC) Product Code. This product code provides an average of 112 product types (markets) per year[2]. Second, we exploit this information and construct product closeness indicators using Jaffe (1986) distance measure and employ an approach similar to Bloom et al. (2013) to construct a pool of product market spillover indicators capturing product market

[2]The four-digit ISIC product code disaggregates the two-digit ISIC industry product, for instance, Food and beverages into the more detailed product levels so that bread and wine which are considered to belong in one industry in the two-digit ISIC industry code are now treated as different product groups (markets).

competition at a four-digit product classification level. The closer the nature and type of product firms are producing (selling), the greater the competition. Foreign firms' interaction with domestic firms in the same product market may lead to market-stealing effects if domestic firms fail to respond to the presence of foreign firms by adopting new technology and increasing their productivity. We hypothesize that FDI has a negative competition effect in a sector where firms are competing in the same product markets, while a positive technology spillover effect prevails in a sector where the competition is in related and distant (not the same) product groups.

Ethiopia provides a unique opportunity to investigate the technology transfer and competition effects of FDI on manufacturing firms for the following reasons. First, Ethiopia is one of the fastest-growing African economies with an average growth record of 10.9% for more than a decade; which is dubbed by Moller & Wacker (2015) as "Ethiopia's great run". The growth has been credited to substantial public infrastructure investment (Moller & Wacker 2017) and aims to bring structural transformation and support the industrial development policy introduced in 2002. Second, the 2012 investment proclamation stressed FDI as a vital pillar of Ethiopia's industrial development strategy and aimed at increasing the inflow of FDI and achieving technology transfer to increase domestic firms' productivity. Over the period 2012 to 2017, for instance, total FDI flow increased from $278.6 million to $4.02 billion(Bank 2021). Third, the manufacturing firms in Ethiopia, however, are believed to be concentrated in industries where technological sophistication is low, and domestic firms may fail to compete "neck and neck" with their foreign counterparts. As indicated in (Nafziger 1990) foreign firms can easily penetrate such a market environment obliterating domestic firms through intense competition and lending market powers to foreign firms.

We estimate a model of total factor productivity for Ethiopian domestic firms where we include FDI and FDI-weighted market spillover - capturing the competition effect of FDI. To address the potential endogeneity of our variables of interest, we use an instrumental variable(IV) estimation technique and employ Two Stage Least Square(2SLS) regression to identify the causal impact of FDI on technology spillover and competition. The choice of instruments is based on economic theory on exchange rate movements, the flow of FDI and production costs. The result from the IV estimation technique indicates the presence of quantitatively significant positive technology and negative competition spillover effects from FDI in Ethiopian manufacturing firms between 2013-2017. This positive technology spillover effect is considerably larger than the negative product market rivalry effect of FDI. The result confirms that horizontal FDI can have a differential impact on knowledge transfer to domestic firms within a sector, depending on the product markets in which foreign firms are competing with domestic firms. Specifically, the result shows that a 1% increase in horizontal FDI raises the productivity of domestic firms by about 6.8% in sectors where foreign firms are competing in distant(related but not the same) product markets. We interpret this result as capturing the technology transfer effect of FDI

On the contrary, a 1% increase in competition (the product closeness-weighted FDI) decreases the productivity of domestic firms competing in the same product group by 0.1%. The IV results support the causal impact of FDI on technology and competition spillover to domestic firms. These results are robust to alternative specifications based on different measures of productivity, competition, and FDI. Examining the heterogeneous effect of FDI also reveals a positive technology spillover effect of FDI on domestic firms working in the manufacturing industries designated as priority sectors by the Government of Ethiopia. Though this finding supports the country's industrial development strategy, the economic impact is modest compared to the overall total factor productivity growth achieved by the manufacturing sector during the study period.

This paper contributes to the technology transfer literature in three different ways. The reliability of evidence for the existence of technology spillovers depends crucially on the plausibility of the proxies employed. This paper, first, disentangles the two counter-acting effects of FDI by constructing a product-closeness indicator in a developing country, Ethiopia. Fons-Rosen et al. (2017) used a similar approach to separate the two effects in six European countries based on the technological closeness of firms constructed using patent information. Patent information helps to group firms into similar patent classes that are technologically close. In developing countries, however, the availability of patent information is limited due to the low level of development of the manufacturing sectors and the subsequent lack of product innovation that is new to the industry (Barrios et al. 2011). In the absence of patent information, product closeness thus provides insight into the true impact of FDI in developing countries as it helps capture the level of competition in the same product group.

Second, the study relates to the literature investigating the technology spillover effect of FDI in both developed and developing countries. Most studies in developing countries, however, fail to establish a positive effect of horizontal FDI(see Aitken & Harrison 1999, Javorcik 2004, Lu et al. 2017). This study adds to this literature by reexamining the issue in Ethiopia and establishing the causal impact of FDI on technology spillover to domestic firms using the instrumental variable approach. Similar results have been found for Mexico (Sjöholm 1999) and China(Liu 2008). Third, it contributes to the literature studying the knowledge spillover from FDI in Africa. The few studies focused on Africa using firm-level data found either negative or no knowledge spillover effect of FDI. For South Africa, Mebratie & Bedi (2013) found no spillover effects of FDI on labor productivity. Bwalya (2006) also finds no significant intra-industry spillovers of FDI in Zambia. Waldkirch & Ofosu (2010) find that the presence of foreign firms in a sector hurts domestically owned firms. Knowledge transfer from FDI to domestic firms in Africa is associated with the geographic proximity of domestic firms to foreign firms (Abebe et al. 2022) and inter-industry knowledge spillovers through linkages (Bwalya 2006). Contrary to previous works, this paper provides evidence for a positive technology spillover effect of sectoral FDI on domestic manufacturing firms in Africa using firm-level data.

The remainder of this chapter is structured as follows. The following section presents the literature review. Section 3 lays out the empirical approach. Section 4 describes the data source and presents some descriptive statistics. Estimation results are presented in section 5, and section 6 provides the concluding discussion.

## 1.2 Literature review

Foreign firms are supposed to have inherent technological and scale advantages that allow them to produce more efficiently and access international markets (Blomström & Kokko 1998, Hymer 1976). Foreign firms also identify and implement systems that increase productivity. Theoretical models of technology spillovers from FDI suggest that knowledge transfer could be achieved through labor turnover from foreign to domestic firms (Fosfuri et al. 2001, Glass & Saggi 2002), through observation and learning that motivate domestic firms to copy or adapt new production technologies (Findlay 1978, Walz 1997) or by establishing business relations which lead to more investments in human capital (Wang 1990). A recent theoretical model also indicates that foreign firms are willing to transfer some of their technological capital (knowledge) in exchange for access to the domestic market (Holmes et al. 2015).

Recent studies on technology spillover from FDI to domestic firms for developed countries suggest the existence of positive technology spillover of FDI. For instance, Haskel et al. (2007), based on plant-level panel data for UK manufacturing from 1973 through 1999, finds a robust and significantly positive technology spillover of sectoral FDI in UK domestic manufacturing firms. Keller & Yeaple (2009) find that FDI leads to significant positive technology spillover for US manufacturing firms. Looking at Japanese regional FDI in the United Kingdom electronics industry, Girma & Wakelin (2001) find a positive correlation between FDI and domestic firms' productivity. Using patent citation data for Japan's FDI in the United States, Branstetter (2006) finds evidence that FDI enhances knowledge flows (innovation). Mariotti et al. (2015) also find that spatial proximity and co-location of domestic firms with foreign firms have a positive impact on productivity spillovers from international affiliates to local domestic suppliers and customers in the service industry in Italy.

In contrast, the results for developing countries are mixed. The early works of Haddad & Harrison (1993) show that increased industry-level FDI is correlated with lower domestic plant productivity in Moroccan manufacturing firms. Aitken & Harrison (1999) find the same negative result for Venezuelan manufacturing firms. Product market competition is often mentioned as a possible explanation for the negative technology spillover effect of FDI (Aitken & Harrison 1999, Djankov & Hoekman 2000, Konings 2001). Recent studies in Africa have also found inconclusive results. Using two-period (2003 and 2007) firm-level panel data from South Africa, Mebratie & Bedi (2013) find that FDI has no spillover effect on the labor productivity of domestic firms. Using firm-level data between 1993 and 1995 for the Zambian manufacturing industry, Bwalya (2006) finds positive and significant inter-industry knowledge spillover from FDI but no intra-industry spillover. Based on a survey of over 200 manufacturing firms in the early to mid-1990s Ghana, Waldkirch & Ofosu (2010) find that foreign firms' presence in a sector hurts domestically owned firms' labor productivity and total factor productivity. Abebe et al. (2022), using district-level information in Ethiopia, find that opening new foreign manufacturing firms in the local area increases the productivity of domestic firms in that locality more than others, confirming the importance that the geographical proximity of foreign firms to domestic firms has for the technology transfer.

Puzzled by the absence of positive intra-industry spillover from FDI, some empirical works considered the technology spillover operating across industries. Based on the analysis of firm-level data from Lithuania, Javorcik (2004) finds positive productivity spillovers from FDI taking place through backward FDI while horizontal FDI is absent. According to Javorcik & Spatareanu (2008), FDI hurts the performance of Romanian manufacturing firms in the same industry, while vertical spillover between foreign affiliates and domestic suppliers has a positive impact. They noted, however, that the spillover effect might be ascribed to either the benefits of scale economies enjoyed by multinational suppliers or the consequences of greater competition caused by foreign entry into the product market.

According to Keller (2010), one possible reason for the negative spillover effect could be the failure to account for the endogeneity of FDI. Using China's WTO membership at the end of 2001 as an exogenous relaxation of FDI regulations and firm-level data, Lu et al. (2017) confirms that FDI in the same industry hurts domestic firms' productivity. They associate the negative spillover with the distance of domestic firms relative to foreign firms' locations. In recent work, Fons-Rosen et al. (2017) use technology closeness to isolate the two countervailing effects of FDI in six European countries and find that FDI has positive spillovers only when foreign and domestic firms use similar technologies while the negative competition effect is dominant in sectors where firms are technologically distant.

The literature also indicates technology transfer depends on various firm characteristics. Firm size is one such factor but with different implications. The relatively larger firms may have the capacity to react to the presence of foreign firms and compete with them through the adoption of (investment in) new technologies (Crespo & Fontoura 2007). Jordaan (2011) shows that firm size is positively related to Mexican domestic firms' capacity to absorb FDI spillover. On the contrary, for UK manufacturing firms, Girma & Wakelin (2007) indicate that smaller firms with a higher proportion of skilled labor benefit from FDI because they have the most to learn technologically. For US manufacturing firms, Keller & Yeaple (2009) find that smaller firms with low productivity benefit more from FDI spillovers than larger productivity firms.

The views on the role of the level of a firm's technology use in knowledge spillover are also inconclusive. According to Findlay (1978), because of the potential for large marginal returns, firms with low levels of technology adopt new technology more rapidly while firms with high technology do not have the incentive to change their current production technologies as they can easily compete with foreign firms. The counter argument outlined by Glass & Saggi (1998) suggests that high-tech firms have the human capital and technical skill to catch up with foreign firms, while low-tech firms that lack these competencies are less likely to. To understand the role of technology use in the FDI knowledge spillover in England, Keller & Yeaple (2009) grouped firms into high-tech and low-tech industries based on their average R&D intensity. They find that firms in high-tech industries adopt new technology and benefit from FDI more than firms in low-tech industries. Barrios et al. (2011) also use R&D to define absorption capacity for Spain and find that it does not have an effect on technology transfer for firms using R&D. The absorption capacity of domestic firms, defined as the gap in total factor productivity (TFP) between the domestic establishment and the industry leader, has an effect on technology transfer of FDI (Girma 2005, Blalock & Gertler 2009).

Developing countries are thus of particular interest to examine the two possible counteracting effects of FDI and how these effects vary by different firm or industry characteristics. First, many developing countries commit a substantial amount of resources to attract FDI (Haskel et al. 2007, Nachum 2001). In addition to filling the investment gap, creating employment opportunities, and generating export earnings, for developing countries, FDI is considered a means of industrial development through technology transfer. Second, the level of technology absorption capacity of domestic firms in developing countries is generally considered low. Third, some domestic firms also believe foreign firms steal their market in established products (Gebreeyesus et al. 2017) and consider them a threat to their growth.

Despite the above theoretical predictions and the current flow of FDI to Ethiopia, studies focused on the knowledge spillover from FDI in Ethiopia are rare. In a recent study, Abebe et al. (2022) examines the technology spillover of FDI at the district level by comparing districts with and without FDI. Gebreeyesus et al. (2017), using the survey of manufacturing firms collected by CSS, shows that domestic firms experienced competition from foreign firms leading to the loss of employees and market share. Based on the same survey, Abebe et al. (2022) and Gebreeyesus et al. (2017) show that firms may upgrade their production process due to competitive pressure from foreign firms. None of these studies, however, looked at the intra-industry technology transfer effect of FDI or disentangled the pure technology transfer effect of FDI from the competition effect. This study fills these research gaps and sheds light on the effectiveness of the government's policy in attracting FDI and achieving technology transfer.

## 1.3 Construction of key variables

In this section, we explain how we construct or define the proxies used to measure horizontal technology spillover and product market competition. It has become standard in the literature to use the Javorcik (2004) approach to define horizontal FDI. We follow suit and define FDI as an output-weighted average of foreign equity share (FES) of all firms in the two-digit ISIC industry code of the manufacturing sector. It is calculated as follows:

$$FDI_{st} = \frac{\sum_1^n FES_{fst} \times Y_{fst}}{\sum_1^n Y_{fst}}$$

where $FDI_{st}$ measures the foreign equity share $FES_{fst}$ of firm $f$ of sectors $s$ at year $t$. $Y_{fst}$ refers to the gross output of a firm measured in terms of operating revenue. Foreign firms may enter foreign markets either to take advantage of the lower production costs (eg., Helpman 1993, Lai 1998) or to get access to the domestic market (eg., Holmes et al. 2015). Following the literature on firm-level productivity (eg., Lu et al. 2017, Javorcik 2004), we use the firm's total output (operating revenue) in the variable construction because the FDI spillover effect may come both from domestic sales and exports.

The empirical literature has shown that technology transfer from R&D (Bloom et al. 2013) and FDI depends on the technology closeness of firms and the level of competition in the product market (Fons-Rosen et al. 2017). The competition in the product market depends on how close (similar) firms' products are in the market. The construction of a product closeness index requires the categorization of each firm's product sales into different product groups or classes (Bloom et al. 2013). LMSMI includes firm's main product sale in a four-digit ISIC industry product code, which consists of 112 product groups that firms compete with. On average, each firm shows sales in 3.1 different four-digit product codes each year. The construction of product market closeness is based on the firm's sales revenue in these different product classes.

We calculate the time-invariant average share of sales per product group for each firm as our measure of activity by product group. For each firm f, we define the vector $m_f = (m_1, m_2, m_3, ...m_{112})$ where $m_f$ is the share of sales of firm f across the different four-digit product markets. The product closeness $PC_{fj}$ between firm f and j at time t measures the unscented correlation of vectors of firms' sales share, $g_f$ and $g_j$, and is calculated following Jaffe's (1986) distance measure:

$$PC_{fj} = \frac{g_f {g_j}'}{(g_f {g_f}')^{1/2} (g_j {g_j}')^{1/2}}$$

The index ranges between zero and one depending on the degree of overlap in the market where firms operate and is symmetric to firms' order so that $PC_{fj}$=$PC_{jf}$. This variable measures distance (similarity) between products in the product market space. We thus use the Bloom et al. (2013) approach to construct the pool of product market spillover(PMSpill) for firm $i$ as a weighted sum of the product closeness of firms $f$ and $j$:

$$PMSpill_{fst} = \sum_{f\neq\ j} PC_{fj} * RS_{jt}$$

where $RS_{jt}$ is all rival firms' sales used as a weight. Note that $PC_{fj}$ is time-invariant but $PMSpill_{fst}$ varies over time because the sales revenue of rival firms (both domestic and foreign firms) change over time. The more products are similar, the greater the competition. When sales by product market rivals increase it depresses a firm's revenue and even pushes a firm to exit the market if it fails to respond to rival firms' presence in a particular product market.

We define the product closeness-weighted horizontal FDI as the product of firm-level product market spillover and the share of output-weighted FDI:

$$FDIComp_{fst} = (FDI_{it} \times PMSpill_{fst})$$

This variable captures the possible competition spillover effect of FDI because of the presence of foreign-owned firms in a sector where firms are competing in the same product group that is identified using the four-digit product code of the manufacturing industry in Ethiopia.

The above Jaffe (1986) measure of product market closeness treats product markets as independent of each other and assumes that product market spillover(interactions or competition) occurs only within the same product group. This is restrictive because a related product market in one area is more likely to benefit from related product market information, and market knowledge spillover across product market fields depends on the level of market aggregation. As a result, competition is more likely to occur in related product groups. This is particularly important when products are substitutes. Product market rivalry between substitute products can lead to profit reduction. We thus assume that firms compete not only in the same product group but also across related product groups and construct competition spillover using the Mahalanobis distance measure to identify the distance between different product groups. The Mahalanobis distance measure between firms uses the similarity of various product groups within firms. The idea is that firms internally identify product groups that have similar characteristics. This distance measure identifies the distance between different product groups based on the frequency with which products are sold in different groups by the same firm and helps to measure the competition between firms not only in the same but also related (distant) product groups.[3]

## 1.4 Data source description

The empirical analysis in this study is based on the 2013 - 2017 annual LMSMI survey data collected by the Ethiopian Central Statistics Service (CSS). The census includes all manufacturing establishments: State-Owned Enterprises (SOEs) and private firms that employ ten persons or more and use power-driven machinery. The data set contains the basic information for each surveyed establishment such as its identification number for each survey year, location code, sector class (industry), ownership structure (including ownership of capital by foreigners which is used to calculate the foreign equity share), and operational information such as sales by four-digit ISIC product code (which is used to construct the product closeness measure in the product market), export, employment, material inputs, fixed assets, and total wage bill.

To calculate the sectoral level of FDI, this study uses the two-digit ISIC (15–36 ) industry code and group manufacturing establishments by industry. FDI is calculated based on the share of total (initial and current) paid-up capital contributed by foreigners to the firm's total paid-up capital and weighted by industry output. Yet, the number of manufacturing firms engaged in the relatively technologically intensive industries (ISIC 30 - 33), Tobacco (ISIC 16), and Refined petroleum products (ISIC 23) are either absent

[3]To calculate the product closeness measure and product market spillover, we customized the Stata routine developed by Bloom et al. (2013)

or too small to apply the total factor productivity estimation techniques discussed below to these industries. We thus exclude Tobacco and refined petroleum products from the analysis while we merge sectors from ISIC 30 to ISIC 33 into one as the Office, computing, and electrical sectors.

The problem with the LMSMI data is that they lack a consistent panel identifier from 2012 to 2017. Each year, an establishment is identified by the combination of its ISIC code and establishment number. The establishment number is unique within each ISIC group and for each LMSMI survey round but it is not necessarily consistent over the years. Creating panel data using the different rounds of LMSMI firm-level datasets requires cross-verification of the establishment's identities across different data sources and years. We use panel identifiers obtained from the Ethiopian Policy Research Institute (PSI) to create panel data. The panel identifiers were created by a group of researchers from PSI and Oxford University and largely relied on firm ISIC code, establishment number, phone number, and establishment name; and were used by Gebrewolde et al. (2022) and Diao et al. (2021).

Based on this panel identifier, we obtained an unbalanced panel which includes almost 73% of firms surveyed during 2013 – 2017 and constitutes 9,460 observations. We then undertake a data consistency and data cleaning process. First, we focused on labor (employment), capital, material, other input costs, and output that are used to estimate the firm's total factor productivity. Each year establishment data is then merged with firms' detailed product group data used to construct the product market competition measure. Other observations with inconsistent values such as negative values are excluded from the analysis. After the data cleaning process, and winsorizing the resulting data for possible outliers at the $1^{th}$ and $99^{th}$ percentiles, the final data constitute an unbalanced panel with 2,545 unique manufacturing firms and 7,764 observations. The number of firms per year varies from a low of 1,148 in 2013 to a high of 2,039 in 2017. On average firms are observed for 3.1 years. Foreign firms account for 5.2% of the observation. However, foreign firms declined by 23% from 74 in 2013 to 57 in 2016. This decline could be attributed to the political violence that erupted in the Oromia region in 2014/15 and intensified in

Table 1.1: Sectoral distribution of FDI in Ethiopia between 2013 – 2017

| | (1) 2013 | (2) 2014 | (3) 2015 | (4) 2016 | (5) 2017 |
|---|---|---|---|---|---|
| All Manufacturing | 19.50 | 26.90 | 20.44 | 7.33 | 16.05 |
| Food and beverages | 17.95 | 20.70 | 16.14 | 4.61 | 22.36 |
| Textiles | 15.38 | 17.19 | 37.73 | 9.34 | 4.65 |
| Garment | 34.21 | 43.68 | 3.69 | 4.80 | 8.91 |
| Tanning and leather | 26.54 | 40.60 | 18.25 | 6.91 | 28.25 |
| Wood | 3.66 | 2.06 | 18.66 | 0.00 | 9.02 |
| Paper | 37.51 | 40.28 | 23.81 | 53.82 | 0.43 |
| Publishing | 6.72 | 10.55 | 3.35 | 0.00 | 0.00 |
| Chemicals | 10.08 | 12.17 | 17.40 | 5.21 | 16.15 |
| Rubber and plastics | 11.93 | 18.42 | 21.74 | 3.59 | 10.79 |
| Non-metallic minerals | 26.55 | 37.04 | 28.83 | 1.53 | 30.92 |
| Basic metals | 23.40 | 59.98 | 30.71 | 9.29 | 24.20 |
| Fabricated metal | 21.33 | 27.05 | 20.09 | 40.4 | 1 7.13 |
| Machinery and equipment | 44.28 | 0.19 | 3.64 | 0.00 | 0.00 |
| Office, computing, electrical | 0.00 | 56.72 | 0.00 | 3.44 | 2.73 |
| Motor vehicles, trailers | 0.00 | 0.00 | 0.00 | 7.28 | 5.41 |
| Furniture | 4.95 | 6.09 | 5.09 | 8.04 | 2.92 |

N.B.: The table reports the sectoral distribution of FDI over the years 2013-2017. The Ethiopian manufacturing industry's two-digit ISIC classification has 22 classifications. But in the table tobacco is excluded while sectors from ISIC 30 to 33 are merged as Office, computing, and electrical sectors, and sectors from ISIC 34 to 35 are not available.

2016 (see, Table A.1).

Table 1.1 presents the total FDI presence in the Ethiopian manufacturing sector and its distribution within the two-digit manufacturing industries for the full sample of firms. From 2013 to 2017, the share of foreign equity in the manufacturing sector declined by 3.45 percentage points from 19.5%. to 16.1%. The decline in the share of FDI in the sector may be related to the worsening security situation, particularly for foreign investors, in certain areas of the country that were the main centers of FDI, and the fall in the number of foreign firms during the same period (see, Table A.1). There are also considerable

Table 1.2: Summary statistics

| | mean | sd | min | max | count |
|---|---|---|---|---|---|
| log(Value added) | 13.91 | 2 | 4.54 | 22.68 | 7,764 |
| log(Capital) | 13.11 | 4 | 0.00 | 22.80 | 7,764 |
| log(Labor) | 3.32 | 1 | 0.00 | 11.13 | 7,764 |
| log(Intermediate input) | 14.14 | 3 | 0.00 | 21.18 | 7,764 |
| log(TFP) | 7.69 | 2 | 0.23 | 17.29 | 7,764 |
| FDI | 17.34 | 12 | 0.00 | 59.98 | 7,764 |
| FDIComp | 126.22 | 301 | 0.00 | 3188.89 | 7,764 |
| Export intensity | 0.04 | 1 | 0.00 | 93.38 | 7,764 |
| Firm size | 0.51 | 0 | 0.00 | 1.00 | 7,764 |
| Capacity utilization | 1.42 | 8 | 0.00 | 100.00 | 7,764 |
| Herfindahl index | 0.10 | 0 | 0.02 | 0.74 | 7,764 |

N.B.: The summary table shows a minimum of zero for the log of capital, labor, and intermediate input because we include firms in the panel if they are observed for two years through their employment fall below 10 workers.

variations across these industries and over the years. The average foreign equity share in 2013 ranged from zero to 44.2% in 2013. The machinery and equipment industry had the highest share of FDI in 2013 followed by the paper (and paper products) industry (37.5%), the Garments (34.2%), and Other non-metallic minerals industry (26.6% ). The sectoral distribution of FDI has varied over the years. In 2017, the industries with the highest percentage of FDI were Non-minerals (30.9%), followed by Tanning and leather (products) (28.3%) and Basic metals (24.2%). Table 1.2 presents the summary statistics[4]. The total number of firms in the sample is 2,545 of which 6% are foreign-invested firms that are both brownfield and greenfield investments located in industrial parks[5].

The trend of total factor productivity of the manufacturing sector and at the two-digit

[4]The correlation matrix of the variables is presented in Table A.2 in Appendix A

[5]There were only two industrial parks from 2013 to 2017. Of the total of 93 and 11 firms which were located in Eastern and Bole Lemi Industrial Park, the panel data include 23 and 11 foreign firms respectively and they account for 40% of employment in each industrial park (Diao et al. 2021). These foreign firms are greenfield investments and expected to export 100% of their product to the international market.

Table 1.3: Total factor productivity of manufacturing industry by sector

| | (1) 2013 | (2) 2014 | (3) 2015 | (4) 2016 | (5) 2017 | (6) Growth rate |
|---|---|---|---|---|---|---|
| All Manufacturing | 7.10 | 7.40 | 7.61 | 8.01 | 8.00 | 0.18 |
| Food and beverages | 7.14 | 7.49 | 7.67 | 8.22 | 8.37 | 0.25 |
| Textiles | 6.31 | 7.09 | 7.34 | 7.55 | 6.82 | 0.10 |
| Garment | 7.25 | 7.14 | 6.77 | 7.05 | 7.21 | -0.01 |
| Tanning and leather | 6.74 | 7.19 | 7.34 | 8.02 | 8.16 | 0.28 |
| Wood | 7.10 | 7.78 | 7.56 | 7.89 | 8.16 | 0.21 |
| Paper | 7.66 | 7.60 | 8.38 | 8.39 | 8.75 | 0.22 |
| Publishing and printing | 7.43 | 7.52 | 7.83 | 8.16 | 8.60 | 0.23 |
| Chemicals | 7.72 | 7.90 | 8.31 | 8.42 | 8.48 | 0.15 |
| Rubber and plastics | 7.19 | 7.70 | 7.74 | 8.31 | 8.40 | 0.24 |
| Non-metallic minerals | 7.04 | 7.23 | 7.57 | 7.97 | 7.73 | 0.14 |
| Basic metals | 7.69 | 7.75 | 8.66 | 8.65 | 9.07 | 0.28 |
| Fabricated metal | 7.45 | 7.73 | 7.49 | 7.94 | 8.07 | 0.12 |
| Machinery and equipment | 9.38 | 7.99 | 9.94 | 8.00 | 8.20 | -0.24 |
| Office, computing, electrical | 0.00 | 6.35 | 0.00 | 9.32 | 9.21 | 1.84 |
| Motor vehicles, trailers | 0.00 | 0.00 | 0.00 | 9.58 | 8.83 | 1.77 |
| Furniture | 6.69 | 7.07 | 7.32 | 7.53 | 7.91 | 0.24 |

N.B.:Total factor productivity (TFP) is in log form and calculated at a firm level using equation (3). The table shows the average productivity of the manufacturing industry by 2-digit sector, and their growth over the years

industry level is reported in Table 1.3. From 2013 to 2017, the manufacturing industry experienced an average growth rate of 18% of total factor productivity [6]. Looking at the industry productivity growth, the Office, computing, and electrical sectors registered the maximum productivity growth of 184% followed by Motor vehicles and trailers with 177% growth. Garment and machinery equipment nonetheless registered negative productivity growth during the period.

[6]The productivity growth is the average growth rate of individual firm-level TFP estimates over the years. It is calculated using the formula $\frac{log(TFP)_{2017} - log(TFP)_{2013}}{5}$

## 1.5 Estimation strategy

### 1.5.1 Firm-level total factor productivity

Our main dependent variable in the FDI spillover regression presented in equation (3) below is total factor productivity for domestic firms (TFP). We use the Cobb-Douglas production function to estimate TFP and assume that the output of firm $f$ at time $t$ is given by:

$$Y_{fit} = A_{fit} K_{fit}^{\beta_k} L_{fit}^{\beta_l} \quad (1)$$

Taking the log of the production function gives us:

$$Y_{fit} = \gamma + \beta_k lnk_{fit} + \beta_l lnl_{fit} + \alpha_{fit} + \epsilon_{fit} \quad (2)$$

$Y_{ft}$ stands for the nominal value added defined as the difference between gross output (operating revenue) and intermediate input of firm $f$ at time $t$ and deflated to the 2016 real value using GDP deflator obtained from the World Development Indicators (Bank 2021). $lnk_{fit}$, capital, is defined as the book value of all fixed assets owned by a firm at the end of the reporting period deflated to its 2016 real value using gross capital formation deflator from the World Bank Development Indicator. $L_{fit}$ is the total number of workers computed based on the average number of workers reported for every quarter. $\epsilon_{ft}$ is either a measurement error or a production shock that is not observable by the firm before making their input decisions at time t. $\alpha_{ft}$ is the logarithm of physical productivity.

The productivity literature provides different methodologies to estimate firm-level productivity. Olley & Pakes (1996) and Levinsohn & Petrin (2003) are the pioneers in developing approaches that use material and investment respectively as a proxy to estimate the unobserved productivity level. We use the latest approach developed by Wooldridge (2009) to estimate firm-level productivity at a firm level. Wooldridge's method uses materials as a proxy and a system of GMM estimation rather than a two-step estimation.

This estimation technique takes into account the Ackerberg et al. (2015) critique that if labor is hired well before productivity is known, the coefficient on labor input will not be correctly identified in the first step of the estimation.[7]

### 1.5.2 FDI spillover regression

To examine the two countervailing effects of FDI, we first identify the firm's position in the product market space and then construct a product market spillover as a proxy for competition as indicated in Bloom et al. (2013). We then weigh this proxy by sector-level FDI and include it in the FDI spillover regression below. The baseline model is:

$$log(TFP_{fit}) = \delta_1 FDI_{it} + \delta_2 FDICom_{fit} + X_t'\beta + \gamma_f + \gamma_t + \epsilon_{fit} \dots\dots\dots\dots\dots (3)$$

where $log(TFP_{fit})$ is the log of total factor productivity of a firm, $f$ in the industry, $i$, and at year $t$. The estimation equation includes firm fixed effect ($\gamma_f$) and year fixed effects ($\gamma_t$). The firm fixed effect controls for the unobserved characteristics of manufacturing firms such as management quality or experience that may affect a firm's productivity while the year fixed effects capture time-variant policy changes at a country level over the years 2013-2011. $X_t$ is a vector of time-varying firm or industry-level variables that are related to firm absorption capacity and affect firm productivity. These control variables include export intensity, firm size dummy (large or small), capacity utilization (CPU), and Herfindahl index. $\epsilon_{fit}$ is an idiosyncratic error term. The standard errors are robust standard errors and clustered at a firm level [8].

Our main variables of interest are $FDI_{it}$ and $FDICom_{fit}$ which capture respectively

[7]We use the Rovigatti & Mollisi (2018) Stata command, *prodest* with *wrdg* method and $ln_K$ is a state variable, $ln_L$ is a free variable, ln(material input) as a proxy variable, to estimate total factor productivity for each firm.

[8]There are two thoughts about what to cluster to account for serial correlation of the error term. Based on Cameron & Miller (2015) suggestion and the assumption that regressors and error terms of different firms from the same industry are correlated, We need to cluster the standard error at the industry level. However, a significant number of firms change their industry over the sample period and this makes clustering at the industry level impossible. So, we considered the second approach suggested by Abadie et al. (2017). They suggested that clustering should be performed at a level where the outcome of the framework lies. In our case, however, the variables of interest are both at the industry and firm level. We thus undertake the clustering at a crossectional identifier, firm level.

the technology transfer and competition effects of horizontal FDI. These two measures of FDI spillovers, however, are correlated by construction.[9] According to the Frisch-Waugh theorem, when such correlated measures are used in the regression, the regression estimates for each variable reflect the contribution that is orthogonal to each other. That means once we control for the competition effect of FDI through market rivalry measure, horizontal FDI indicates the pure technology transfer effect of FDI. Fons-Rosen et al. (2017) used a similar approach where they used technological closeness to separate the two spillover effects of FDI. The main difference is that we use product closeness instead of technological closeness to separate the two counteracting effects of FDI. Therefore, we expect the coefficient for $FDI_{it}$, $\delta_1$, to be positive capturing the pure horizontal technology spillover effect of FDI in the sector where product market rivalry is low (in a sector where foreign firms are competing in distant(related) product markets). We also expect $\delta_2$ to be negative indicating the pure product rivalry or competition effect of FDI since an increase in the rival firm's sales decreases the firm's revenue and thus productivity. Although it is common to use productivity as a dependent variable in literature, it is important to note that there is no theoretical basis for why increased competition should lower productivity.

Since we are interested in the productivity of domestic firms, equation (1) is estimated for domestic firms, but we report the result for the whole sample as well to see the change in the results for the two samples of firms. The literature uses different cut-off points to define domestic firms. For instance, Javorik (2004) defines domestic firms as firms with less than 10% foreign ownership of capital, while Lu et al. (2017) use 25%, and Haskel et al. (2007) use 20% of foreign ownership as a cut-off to define domestic firms. We define domestic firms as firms that never had any foreign ownership during the sample period. Fons-Rosen et al. (2017) and Du et al. (2011) adopted the same approach to identify domestic firms and estimate FDI spillover.

We first estimate equation (1) using the Ordinary Least Square(OLS) estimation method and the model includes sector and region dummies in addition to the year dummies. Administratively, Ethiopia is divided into nine regional states and two administra-

[9]The degree of correlation between the two variables is 0.21.

tive cities. Most of the manufacturing industries in the country are concentrated in Addis Ababa and nearby cities of the Oromiya region, where foreign firms are also concentrated, for better access to infrastructure or market opportunities. Some regions could also have a locational advantage for raw materials and attract foreign firms for cheap raw material access. The region dummies control for these time-invariant, and unobserved heterogeneity of manufacturing establishments across regions that could be correlated with the error term.

As indicated in the descriptive statistics, the level of productivity across industries is different. This could be related to the unobserved heterogeneity of firms in various industries. In addition, FDI could also flow to industries that are more productive than others or to insutries where firms receive special support from the host country. Since the inception of the industrial policy strategy in 2002, the government of Ethiopia has given special support to priority sectors which include agro-processing, textiles, garment and leather manufacturing because of their comparative advantage. These industries receive easy and cheap access to land (FDRE 2011) and subsidized credit through the Development Bank of Ethiopia (DBE) with only 30% of the equity requirement. We, therefore, include industry dummies to allow for exogenous differences in productivity growth across industries. Yet, the estimates may still suffer due to the endogeneity of both FDI and competition. To overcome this problem, we use an IV 2SLS estimation technique as discussed below.

## 1.6 Estimation Result

We begin our analysis by undertaking an exploratory analysis and estimating the basic model discussed in equation (1). Estimates of firm-level TFP from equation (2) are used as an outcome variable in equation (1). Table 1.4 presents the result from OLS and Fixed Effect (FE) estimation methods for the whole sample of firms, which include both domestic and foreign firms. The result from OLS in column (1) indicates that the sectoral FDI has a negative technology spillover effect but it is insignificant. In column (2) we include the variable measuring product market competition which reveals the competition effect of FDI in the same product group. The technology spillover is still negative and insignificant. The competition effect of FDI is positive but it's insignificant with null magnitude. The result from OLS estimation suggests that an increase in sectoral FDI has no either positive technology spillover effects or a negative competition effect which may result in market stealing and a reduction of productivity for manufacturing firms. Controlling for time-invariant firm-level heterogeneity using the FE estimation technique.[10] presented in columns (3) and (4), gives almost the same result as the OLS estimation method for both the FDI and competition.

The results for other explanatory variables, however, reveal interesting results, but the coefficient estimates in OLS and FE estimation methods are different in magnitude. The coefficient estimates for export intensity are negative and significant in all specifications, without and with the inclusion of the product market competition measure, in both OLS and FE estimation methods. This result conflicts with the general expectation that exporting firms have higher productivity through learning-by-exporting or self-selection into exporting but is consistent with the finding of Abraham et al. (2010) for China. Capacity utilization, which captures a firm's absorption capacity, is negative but not significant in all specification, and estimation methods. Firm size, the other measure of absorption capacity, however, has a positive and significant effect. The result shows that larger firms are more productive than smaller firms. The industry concentration indicator, Herfindahl Index (HI), commonly used as a measure of competition in the literature, is also positive and significant suggesting that an increase in the Herfindahl index, a decline in competition, increases the productivity of firms operating in the concentrated sector.

Table 1.5 shows the same regression results as in Table 4 but for domestic manufacturing firms only. Column (1) and column (2) show the result from OLS regression and the result reveals almost identical estimates as for the whole sample of firms. The result after controlling for time-invariant firm heterogeneity in columns (3) and (4) also shows that though the effect of sector-level FDI on a firm's level of productivity is negative, it is still insignificant. The result is consistent with previous studies which find no technology

[10]The result from the overidentification test supports the fixed effect estimation technique and are presented in Table A.3 in Appendix A.

Table 1.4: Results from OLS and FE regression for the whole sample of firms

| | OLS | | Fixed effect | |
|---|---|---|---|---|
| | (1) log(TFP) | (2) log(TFP) | (3) log(TFP) | (4) log(TFP) |
| FDI | -0.002 | -0.002 | -0.001 | -0.001 |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| FDIComp | - | 0.000 | - | 0.000 |
| | | (0.000) | | (0.000) |
| Export intensity | -0.075*** | -0.075*** | -0.061*** | -0.061*** |
| | (0.004) | (0.004) | (0.005) | (0.005) |
| Firm size | 1.257*** | 1.257*** | 1.281*** | 1.281*** |
| | (0.036) | (0.036) | (0.044) | (0.044) |
| Capacity utilization | -0.000 | -0.000 | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Herfindahl index | 0.630*** | 0.633*** | 0.705** | 0.706** |
| | (0.237) | (0.237) | (0.276) | (0.276) |
| Observations | 7764 | 7764 | 7764 | 7764 |
| Adjusted $R^2$ | 0.229 | 0.229 | 0.233 | 0.233 |
| $\mathrm{R}^2 within$ | . | . | 0.236 | 0.236 |

N.B.: The dependent variable, $\log(TFP_{ft})$ is the log of total factor productivity for firm $f$ in the industry $i$ at time $t$. Column (1) and column (2) show the results obtained using OLS regression while column (3) and column (4) shows the results from fixed effect estimation. All regressions include time, sector, and region dummies. The sample includes all firms. Robust standard errors are given in parentheses and clustered at a firm level and *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

spillover effect of FDI in developing countries (eg., Bwalya 2006, Javorcik 2004, Mebratie & Bedi 2013). The explanation put forward for the absence of knowledge spillover effect in the literature is the low level of local firms' absorptive capacity. Product market competition also has an insignificant null effect on a firm's total factor productivity. Based on the preceding discussions, we conclude that sectoral FDI has neither positive technology spillover nor a negative competition effect on domestic firms in the Ethiopian manufacturing industry.

Table 1.5: Results from OLS and FE regression for domestic firms

| | OLS | | Fixed effect | |
|---|---|---|---|---|
| | (1) log(TFP) | (2) log(TFP) | (3) log(TFP) | (4) log(TFP) |
| FDI | -0.002 | -0.002 | 0.000 | -0.000 |
| | (0.002) | (0.003) | (0.003) | (0.003) |
| FDIComp | - | 0.000 | - | 0.000 |
| | | (0.000) | | (0.000) |
| Export intensity | -0.242** | -0.242** | -0.229 | -0.229 |
| | (0.103) | (0.103) | (0.144) | (0.144) |
| Firm size | 1.252*** | 1.252*** | 1.287*** | 1.287*** |
| | (0.037) | (0.037) | (0.046) | (0.046) |
| Capacity utilization | -0.001 | -0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Herfindahl index | 0.655*** | 0.658*** | 0.839*** | 0.841*** |
| | (0.238) | (0.238) | (0.278) | (0.278) |
| Observations | 7359 | 7359 | 7359 | 7359 |
| Adjusted $R^2$ | 0.223 | 0.223 | 0.232 | 0.232 |
| $\mathrm{R}^2 within$ | - | - | 0.236 | 0.236 |

N.B.: The dependent variable, $\log(TFP_{ft})$ is the log of total factor productivity for firm $f$ in industry $i$ at time $t$. Column (1) and column (2) report results obtained using OLS regression while column (3) and column (4) report results from fixed effect estimation. All regression includes time, sector, and region dummies. The sample of domestic firms comprises firms that have no foreign equity over the years of analysis. Robust standard errors are reported in parentheses and clustered at a firm level, and *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

### 1.6.1 Endogeneity issues

For the fixed effect estimation to yield consistent coefficient estimates, it must be the case that variation in the regressors is exogenous to the productivity of domestic firms. Including dummy variables potentially controls for endogeneity problems that could arise from regional variation, industry productivity differences, and policies implemented at different years at a country level. But there still could be endogeneity problems arising from other factors. FDI could flow to low-productivity firms or industries where foreign firms make easy targets to expand market share. The flow of FDI to these industries could also be related to macroeconomic factors that affect the overall attractiveness of the country and industries to foreign investors. In addition, the product market competition may be endogenous. Failure to account for such factors could bias the spillover estimates and these results can't used to make inferences since the fixed effect estimates are inconsistent.

We therefore use an instrumental variable approach to overcome the endogeneity of FDI and Competition. Our choice of the instrument is motivated by the theory that the depreciation of domestic currency can lead to foreign acquisitions of certain domestic assets (Froot & Stein 1991, Klein et al. 2002). The use of a real effective exchange rate (REER) as an IV for FDI is common in the literature. Keller & Yeaple (2009) used REER interacted with industry dummies as an instrument for FDI in their analysis of FDI technology spillover to U.S. manufacturing firms. Farole & Winkler (2012) used a similar instrument for the analysis of FDI in a cross-sectional country setting. We therefore adopted the same strategy and used REER interacted with industry dummies as an instrument for $FDI_{it}$.

The measure of competition coming from foreign firms, $FDICom_{ft}$, could also be endogenous not only because it is weighted by FDI but competition by itself is a result of firms' market interaction and could be affected by various factors. So we used two instruments for the competition. First, since it is an FDI-weighted measure of competition, we use the same instrument as FDI but now weighted by firm-level product market spillover variable as in Bloom et al. (2013) applied to the firm level. Our second instrument for competition is the cost of starting a business. Ospina & Schiffbauer (2010) used a country-level index for the costs of starting a business as an instrument of competition. So, we construct a similar external instrumental variable for competition based on microeconomic theory relating to the cost of production. If a firm has higher fixed costs relative to the industry, the cost of establishing a business producing the same type of product is high. This restricts the entry of new firms and consequently, the number of firms competing in the same product market. Rival firms' sales revenue will thus be low indicating low-level competition.

In addition, a firm with a high fixed cost relative to the industry must produce at full capacity to achieve a lower unit cost and have a larger market share in the product market, reducing rival firms' revenues. Our instrument is defined as the firm's fixed cost share ($SFC_{fit}$) out of the total industry fixed costs - $(Fxcost_{fit})/(Fxcost_{it})$, where $(Fxcost_{fit})$ is the fixed cost of firm at time t, and $Fxcost_{it}$ is the fixed cost of the industry s at time t. So, $SFC_{fit}$ is assumed to affect product market competition negatively. The instrument is weighted by REER which interacts with the industry dummy since the measure of product market competition is weighted by FDI in the same industry.

The instruments satisfy both the relevance assumption and the exclusion restriction that the instruments affect the outcome variable indirectly. So, the identifying assumptions are, first, the depreciation of the real exchange rate increases the location advantage or competitiveness of a country in receiving FDI which in turn increases the share of firms' FDI in any industry (relevance assumption of the instrument); and, second variations in REER do not affect our outcomes through channels other than the share of FDI (the exclusion restriction condition). These two assumptions also hold for our measure of product market competition in that an increase in the relative fixed costs of a firm increases its market share in the industry and reduces rival firms' sales thereby decreasing competition. The effect of the share of fixed costs on the outcome variable is only through product market competition.

The first stage regressions for both the whole sample and domestic firms from the fixed effect estimation are presented in Table 1.6. The result indicates that two of the three instruments for both samples are highly significant. The real effective exchange rate (REER) is defined as the ratio of the basket of foreign currency to the local currencies. So a rise in the REER is an appreciation of the local currency and is expected to discourage FDI flow. Consistent with the prediction, the result shows that an appreciation of the exchange rate leads to a fall in sectoral FDI for both samples showing the relevance of the instrument. Similarly, product market spillover-weighted FDI has a positive and significant effect on competition. The instrument for competition, the relatively fixed

Table 1.6: First stage result from FE regression

| | Whole sample | | Domestic firms | |
|---|---|---|---|---|
| | (1) FDI | (2) FDIComp | (3) FDI | (4) FDIComp |
| Exchange rate | -0.034*** | -0.852*** | -0.033*** | -0.825*** |
| | (0.002) | (0.076) | (0.002) | (0.078) |
| Weighted exchange rate | 0.000*** | 0.007*** | 0.000*** | 0.007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Relative fixed cost | 0.000 | 0.001 | -0.000 | 0.001 |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| Export intensity | 0.060** | 0.164 | 0.721 | -5.529 |
| | (0.030) | (0.473) | (0.621) | (13.438) |
| Firm size | 0.769*** | 15.545** | 0.638** | 16.302** |
| | (0.265) | (7.436) | (0.275) | (7.856) |
| Capacity utilization | 0.002 | 0.085 | -0.008 | -0.029 |
| | (0.013) | (0.230) | (0.013) | (0.242) |
| Herfindahl index | -11.918*** | -339.944*** | -13.798*** | -371.854*** |
| | (1.803) | (58.465) | (1.884) | (61.270) |
| Observations | 7764 | 7764 | 7359 | 7359 |
| Adjusted $R^2$ | 0.568 | 0.409 | 0.575 | 0.417 |
| $\mathrm{R}^2 within$ | 0.570 | 0.412 | 0.577 | 0.420 |
| F-stat | 76.055 | 187.110 | 70.830 | 177.119 |

N.B.: The dependent variable in column(1) is sectoral FDI and foreign firms' product market competition in column (2). The fixed effect regression includes year, sector, and region dummies. Clustered standard errors are in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

costs of a firm, however, is insignificant with the opposite sign suggesting that a rise in firms' investment in fixed assets increases competition in that it raises rival firms' sales in the product market. The F-stat for the joint significance of the instruments indicates that the instruments are jointly significant for all specifications and confirms the relevance of the instruments.

The result from the IV 2SLS regression and post-estimation specification tests are shown in Table 1.7. Column (1) and column (4) reproduce the FE results for the whole sample and domestic sample respectively, for the sake of comparison. Columns (2) and (3) show the second stage result after using the instrumental variables for the endogenous

Table 1.7: Results from the 2SLS regression

| | Whole sample | | | Domestic firms | | |
|---|---|---|---|---|---|---|
| | (1) FE | (2) IV | (3) IV | (4) FE | (5) IV | (6) IV |
| FDI | -0.001 | 0.011 | 0.054*** | -0.000 | 0.013 | 0.067*** |
| | (0.003) | (0.016) | (0.016) | (0.003) | (0.017) | (0.018) |
| FDIComp | 0.000 | -0.000 | -0.001*** | 0.000 | -0.000 | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Export intensity | -0.061*** | - | -0.065*** | -0.229 | - | -0.278* |
| | (0.005) | | (0.005) | (0.144) | | (0.144) |
| Capacity utilization | 0.002 | - | 0.002 | 1.287*** | - | 0.002 |
| | (0.002) | | (0.003) | (0.046) | | (0.003) |
| Firm size | 1.281*** | - | 1.260*** | 0.001 | - | 1.273*** |
| | (0.044) | | (0.047) | (0.002) | | (0.049) |
| Herfindahl index | 0.706** | - | 1.333*** | 0.841*** | | 1.744*** |
| | (0.276) | | (0.367) | (0.278) | - | (0.403) |
| Observations | 7764 | 7619 | 7619 | 7359 | 7141 | 7141 |
| Adjusted $R^2$ | 0.233 | -0.388 | -0.279 | - | -0.413 | -0.344 |
| F-stat: Sectoral FDI | - | - | 76.055 | - | - | 70.830 |
| F-stat: Competition | - | - | 187.110 | - | - | 177.119 |
| K-P week iden test | - | 87.126 | 69.655 | - | 88.466 | 65.995 |
| A-R weak id P-value | - | 0.035 | 0.000 | - | 0.016 | 0.000 |
| Hansen J p-value | - | 0.012 | 0.011 | - | 0.004 | 0.108 |
| Endogeneity p-value | - | 0.172 | 0.004 | - | 0.152 | 0.000 |

N.B.:The dependent variable, $(\text{TFP})_{fit}$ is the log of productivity of firm f of industry $i$ at time $t$. The table shows coefficients from FE and IV estimation for the full sample and domestic sample. The domestic sample comprises firms that have no foreign participation over the years of analysis. Both the FE and IV regressions include year, region, and sector dummies. Clustered standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

variables for the whole sample, without and with the inclusion of explanatory variables. The result shows that taking care of the endogeneity of FDI and competition variables for the whole sample of firms changes both the significance and magnitude of these variables. In the fixed effect estimation of column (1), the effect of FDI on technology transfer is negative and insignificant. However, after taking care of the endogeneity and without the inclusion of the control variable in column (2) horizontal FDI changes its sign but remains insignificant. After the inclusion of the control variable in column (3) FDI becomes significant at a one percent significance level and considerably increases in magnitude.

Competition, in the fixed effect estimation of column (1) for the whole sample is positive and significant. In the IV estimation of columns (2) and (3) it turns out to be negative; and becomes significant at a one percent significance level when the control variables are included in the model, Column (3). Yet, the Hansen J-statistics for the whole sample show that the model fails the overidentification test that the excluded instruments are not independent of the error process; and thus the instruments are not valid. So, the estimates from the IV 2SLS regression for the whole sample are inconsistent and cannot be used to make inferences.

Column (5) and column (6) of Table 1.7 show the result from the IV 2SLS regression for the sample of domestic firms. The specification test for the sample of domestic firms without the control variables in column (5) indicates that the model fails the overidentification test. However, after including the control variables in column (6), the Hansen J-statistic of 2.59 (p-value of 0.108) strongly rejects the hypotheses that the instruments are endogenous and confirms the validity of the instruments. The Kleibergen-Paap F statistic (65.995) is well above the Stock-Yogo 10 percent critical value and indicates that the instruments are relevant and very strong. The Anderson–Rubin Wald test for weak-identification-robust inference of 6.49 (p-value of 0.000) indicates that the endogenous regressors (instruments) are relevant. The test for exogeneity also confirms the endogeneity of the variables and corroborates the use of the IV approach.

Based on the result from the IV 2SLS regression presented in column (6) of Table 1.7, horizontal FDI has a positive and significant effect on domestic firms' productivity with a relatively higher magnitude. Coming to the competition or product market rivalry effect of FDI, the result indicates that foreign firms' product market rivalry has a negative spillover effect and reduces the firm's productivity. The result confirms that, in the absence of an instrumental variables approach, one would underestimate the true effect of technology transfer and the competition effect of horizontal FDI on productivity. We therefore conclude that horizontal FDI increases technology spillover to domestic firms in a market where foreign firms are competing in related (different) product groups with relatively low levels of competition. The result is consistent with what Girma & Wakelin

(2001) find in the UK where technology spillover occurs for firms that face low competition from their foreign counterparts. The result specifically shows that a 1% increase in sectoral FDI raises the productivity of domestic firms in the sectors where firms are competing in distant (related) product markets by about 6.7%.[11] Our finding is consistent with the positive technology spillover effect from FDI to local firms that Abebe et al. (2022) find in Ethiopia. However, our approach and focus are different. We focus on isolating the intra-industry technology transfer of FDI controlling for the product market interaction of firms. The prevalence of a positive technology spillover effect of FDI within related product groups could be considered evidence that knowledge transfer from FDI could be present in upward and downward-linked firms within a sector.

The literature on FDI indicates various channels of knowledge transfer. So, what is the channel for this intra-industry technology spillover of FDI? Defining supply-linked domestic firms as those that generate at least 10% of their sales revenue from sales to FDI firms directly in 2013.[12] Gebreeyesus et al. (2017) indicate that 7.5% of domestic firms are supply-linked. Of these supply-linked firms, 46% report improved their production techniques/processes due to competition while 21% directly adopted production techniques/processes by observing or copying from foreign competitors. They further showed that 7% of domestic firms are labor-linked- recruited workers who were previously employed by FDI firms. using the same cross-sectional data Abebe et al. (2022) also show that 29.9% of domestic firms have at least one type of linkage with foreign-invested firms.[13]

It is possible that these linkages could be backward and forward linkages outside of an industry. Yet, within-indstry competition is the major reason for technological upgrading.

[11]Had there not been a decline in the number of foreign firms over the study period, this positive spillover effect of FDI could also have been higher. The result for the competition effect of FDI discussed below, may have also been economically significant. The result for the competition effect of FDI, discussed below, could have also been economically significant.

[12]Their study is based on the supplementary census of manufacturing firms on technology transfer. This census was carried out for 2013 only and included questions on whether domestic firms encounter competition in the product market and labor market, and the various mechanisms through which knowledge transfer occurred. Details can be found in Abebe et al. (2022) and Gebreeyesus et al. (2017).

[13]These linkages include whether domestic firms (i) Faced competition from foreign plants in output markets, (ii) Faced competition from foreign plants in labor markets, (iii) Hired labor previously employed by foreign plants, (iv) Purchased inputs from foreign plants, and (v) Sells inputs to foreign plants.

The 2013 survey of technology transfer survey of manufacturing firms reveals that 15.4% of domestic firms in Ethiopia upgrade their production process due to direct competition from foreign firms in their established product while 10.2% of them achieve the technology transfer through observation and directly adopting (copying) the production techniques of foreign firms (Abebe et al. 2022). This is contrary to what John (2016) finds for sub-Saharan African manufacturing firms where the majority of knowledge transfer is stipulated in contracts between foreign firms and domestic firms.

The positive technology spillover effect of FDI is, however, offset by its product market rivalry effect in sectors where firms are competing in the same product markets. An increase in competition by 1% reduces the productivity of domestic firms by 0.1% in sectors where firms are competing in the same product group. Though the magnitude is small the result is consistent with the survey report by Gebreeyesus et al. (2017) which indicates that domestic firms experienced stiff competition from foreign firms in the product market that led to a decline in sales revenue. The small product market rivalry effect of FDI could be related to the adoption of new production technologies by domestic firms in response to foreign firms' competition in their established products (see Abebe et al. 2022, Gebreeyesus et al. 2017).

Looking at the effect of the explanatory variables on firm-level productivity reveals an interesting result. Contrary to our expectation, export intensity turned out to be negative and significant at a 10% significant level, indicating that an increase in the share of a firm's export decreases a domestic firm's productivity. The result is consistent what (Abraham et al. 2010) find for Chinese manufacturing firms; and suggests export volume doesn't matter for a firm's productivity. Firm size has a positive and significant effect on firm-level productivity at a 1% significant level suggesting that larger firms are more productive than smaller firms. This result is consistent with the stylized findings of the literature that firm size is related to heterogeneous firm-level productivity (see, Jordaan 2011, Melitz 2003). Capacity utilization has a positive but insignificant effect on firm-level productivity. This result is also consistent with Keller & Yeaple (2009) findings for USA manufacturing firms. Finally, the result shows a positive and statistically significant relationship between industry concentration and domestic firm's productivity implying that an increase in industry concentration (reduction in industry competition) increases firm-level productivity.

After establishing the presence of spillover effects of FDI and the transmission mechanisms, we next discuss the magnitude of the economic impact of technology and product market rivalry effects on productivity growth as suggested by our estimates. As indicated in Table 1.1, the share of total FDI in Ethiopian manufacturing declined from 19.49% in 2013 to 16.05% in 2017. Based on the total factor productivity estimates of equation (3) presented in Table 1.3, the average manufacturing sector productivity growth over the sample period is 18%. The mean technology spillover estimates for domestic firms indicated in column (6) of Table 1.7 is 0.067. This indicates that the Ethiopian manufacturing sector has lost 1.05% productivity growth that could have been obtained from FDI technology spillovers over the period had the FDI level remained at the 2013 level. Similarly, the decline in FDI over the period contributed to 0.02% of the productivity growth over the same period through competition. With a productivity growth of 18% observed over the study period, the estimate of the contribution of FDI technology spillover to this growth is quite small. Similarly, the gain in productivity obtained from the decline in competition effect of FDI is negligible.

### 1.6.2 Robustness of the result

We undertake four robustness analyses to check whether the main result shown in column (6) of Table 1.7 holds for other measures of productivity, product market rivalry, FDI measures, and the sample. The first stage regression results for these measures are presented in Table A.3 of Appendix A. Table 1.8 presents the result from these robustness exercises. Column (1) replicates our preferred IV regression when TFP is calculated using the Wooldridge (2009) approach and product market rivalry is measured using Jaffe's (1986) distance measure. In the first robustness exercise, presented in Column (2), the outcome of interest, TFP, is now calculated using the Ackerberg et al. (2015), (ACF, hereafter), approach. The result confirms a positive and significant intra-industry technology spillover effect of FDI at a 1% significance level. Likewise, the competition effect of horizontal FDI is negative and significant at a 1% significance level with a similar magnitude. However, the Hansen J-statistics for the overidentification test indicates that the model is not identified at a 10% significance level.

Table 1.8: Robustness result

| | (1) Jaffe | (2) ACF | (3) Mahalanobis | (4) FDI-Emp't | (5) AA & Oromia |
|---|---|---|---|---|---|
| FDI | 0.067*** | 0.060*** | 0.063*** | 0.270** | 0.087** |
| | (0.018) | (0.017) | (0.017) | (0.110) | (0.039) |
| FDIComp | -0.001*** | -0.001*** | -0.004*** | -0.001* | -0.001** |
| | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) |
| Export intensity | -0.278* | -0.286** | -0.275* | -0.446** | -0.312** |
| | (0.144) | (0.143) | (0.144) | (0.220) | (0.158) |
| Capacity utilization | 0.002 | 0.002 | 0.002 | 0.003 | 0.002 |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.003) |
| Firm size | 1.273*** | 1.303*** | 1.271*** | 1.133*** | 1.243*** |
| | (0.049) | (0.047) | (0.049) | (0.095) | (0.082) |
| Herfindahl index | 1.744*** | 1.593*** | 1.674*** | 0.711* | 0.987* |
| | (0.403) | (0.390) | (0.385) | (0.427) | (0.524) |
| Observations | 7141 | 7141 | 7141 | 7141 | 3494 |
| Adjusted $R^2$ | -0.344 | -0.276 | -0.326 | -1.292 | -0.589 |
| F-stat: Sectoral FDI | 70.830 | 70.830 | 76.138 | 4.794 | 10.599 |
| F-stat: Competition | 177.119 | 177.119 | 158.742 | 153.652 | 63.165 |
| K-P week id stat | 65.995 | 65.995 | 75.145 | 3.615 | 9.819 |
| A-R weak id P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.013 |
| Hansen J p-value | 0.108 | 0.061 | 0.100 | 0.149 | 0.185 |
| Endogeneity p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.017 |

N.B.: The table reports results from IV estimation based on different product-market closeness and productivity measures. All regression includes year, region, and sector dummies. Column (1) shows benchmark results while column (2) shows results based Ackerberg et al. (2015) productivity estimate while column (3) is based on Mahalanobis' distance measure. Clustered robust standard errors are in parenthesis. The p-values of specification tests are the K-P Week identification test, the F-test for weak instruments, the Hansen-J statistics test for the validity of overidentifying restriction, and the test for the exogeneity of the excluded variables

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

In the second robustness check, presented in column(3), the Mahalanobis' distance measure is used to construct product market competition. Unlike Jaffe's (1986) measure of competition, the Mahalanobis' distance measure assumes that competition is not restricted to the same product group but also to related product groups. The coefficient estimate for FDI is still positive and significant at a 1% significant level. The estimated coefficient for the competition effect of FDI using Mahalanobis' distance measure in column (2) is also significant at the same significant level. These results are similar to the results presented in column (1) when Jaffe's (1986) distance measure is used to construct competition. This suggests that the level of product market competition in the same product group and related product groups is equivalent, or the absence of high product differentiation within a sector in the Ethiopian manufacturing industry.

In the third robustness exercise, the paper uses sector labor FDI as defined in Aitken & Harrison (1999) where the share of foreign equity of a firm in an industry is weighted by the share of each firm employment in the total industry employment.[14] Column(4) of Table 1.8 presents the result for employment-weighted FDI. The coefficient estimate for FDI is positive and significant at a 5% significant level. Compared to the other estimated effect of FDI discussed earlier, the effect of FDI using Aitken & Harrison's (1999) measure has a significantly larger effect. Yet, the heteroscedastic robust Kleibergen & Paap (2006) F-test fails to reject the null that the model is weakly identified. Further tests for weak instruments based on the first stage indicate that the standard F-stat of 4.79(p=0.000). The Anderson-Rubin Weak-identification-robust-inference test, however, indicates that the endogenous regressors (instruments) are relevant.

Most foreign firms are believed to be concentrated in some districts and big cities. It is therefore possible that both the technology spillover and competition effect of FDI could be stronger for firms located in these areas due to the agglomeration effect. Along these lines, Abebe et al. (2022) investigate the agglomeration effect of FDI in knowledge transfer by comparing the change in TFP of domestic plants in districts where a large greenfield foreign plant was operational with districts where FDI in the same industry was licensed but not yet operational. Their result indicates the presence of FDI knowledge spillover to domestic firms due to the geographical proximity of domestic firms to foreign firms.

In this spirit, we estimate equation (1) by restricting our sample to the two regions, Addis Ababa (AA), the Capital City, and the Oromia region, which includes the outskirts

[14]The calculation of FDI in Aitken & Harrison (1999) is given by $FDI_{fit} = \frac{\sum_1^n FES_{ft} \times Empt_{fit}}{\sum_1^n Empt_{fit}}$

of Addis Ababa. In the sample period, the two regions account for around 89% of foreign firms in the country. The result in column (5) of Table 8 presents IV 2SLS for Adiss Ababa and Oromia region only. The result confirmed that the technology spillover from FDI is still positive and significant at a 1% significant level. The magnitude is relatively higher than the sample of domestic firms for the whole country. Similarly, the competition effect of FDI is still negative and significant at a 1% significant level. The magnitude is also the same as the sample of domestic firms for the whole country. The heteroscedastic robust Kleibergen & Paap (2006) F-test, however, fails to reject the null that the model is weakly identified for the restricted sample of two regions, but the standard F-stat reported in Table A.4 indicates the relevance of the instruments. The Anderson–Rubin weak-identification-robust test also indicates that the endogenous regressors (instruments) are relevant,

## 1.7 Heterogeneous effect of FDI

In the preceding analysis, we found that there is indeed an intra-industry technology transfer effect of FDI in domestic firms which outweighs its competition spillover effect. But, who benefits most from this technology transfer? Does the effect vary by industry to which firms belong or by the technology sophistication of firms? In this section, we look at whether the technology transfer and competition effect of FDI is heterogeneous in two dimensions: government policy focus and industry-level technology use. In 2002, Ethiopia implemented an industrial development strategy that provides special attention and preferential policy support to industries that are identified as priority industries. We therefore divide the manufacturing sectors into priority industries and other industries (see, Table A.5) for the list of industries that belong to the two groups. These industries have been chosen as priority sectors because of their relative advantage and potential to provide a competitive edge to the nation in the international market due to their linkage with both the agriculture and manufacturing sectors. Though these industries are considered low-tech by international standards, the inflow of FDI to these industries is expected to benefit domestic firms through labor mobility or competition.

Table 1.9: Heterogeneous effect of FDI

| | (1) All domestic firms | (2) Priority sector | (3) Other sector | (4) Hight Tech | (5) Low Tech |
|---|---|---|---|---|---|
| FDI | 0.067*** | 0.012* | -0.006* | -0.006 | 0.009 |
| | (0.018) | (0.007) | (0.003) | (0.004) | (0.006) |
| FDIComp | -0.001*** | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Export intensity | -0.278* | -0.258 | -0.137 | -0.114 | -0.300 |
| | (0.144) | (0.189) | (0.182) | (0.188) | (0.188) |
| Capacity utilization | 0.002 | 0.004 | 0.000 | 0.000 | 0.004 |
| | (0.003) | (0.004) | (0.003) | (0.003) | (0.004) |
| Firm size | 1.273*** | 1.419*** | 1.205*** | 1.169*** | 1.437*** |
| | (0.049) | (0.080) | (0.057) | (0.060) | (0.073) |
| Herfindahl index | 1.744*** | 0.764 | 0.776** | 0.784** | 0.960* |
| | (0.403) | (0.558) | (0.331) | (0.338) | (0.521) |
| Observations | 7141 | 2913 | 4446 | 3976 | 3383 |
| Adjusted $R^2$ | -0.344 | 0.235 | 0.243 | 0.242 | 0.238 |
| $\mathrm{R}^2 within$ | - | 0.241 | 0.248 | 0.247 | 0.244 |
| K-P Week id test | 65.995 | - | - | - | - |
| Hansen J p-value | 0.108 | - | - | - | - |
| Endogeneity p-value | 0.000 | - | - | - | - |

N.B.: The table shows results from fixed effect estimation for a different group of firms, The dependent variable is log of total factor productivity, $(TFP)_{fit}$, and the sample comprises domestic firms that do not have any foreign capital in a given year. Column (1) shows benchmark results from IV estimation while Column (2) reports results for priority sectors and Column (3) shows results for other sectors. Column (3) shows results for low-tech groups of firms and column (4) shows results for firms that use sophisticated technology.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Second, the level of R&D that firms undertake in developing countries is almost non-existent, and the LMSMI census also does not have such information to identify firms by the level of technology use. We thus resort to NACE Rev.2, industrial classification, and the level of industrial technology assignment in the NACE Rev.2. The problem with this approach is that Ethiopia does not have a standard measure to group firms into high and low-tech industries. We therfore use the European statistical classification of economic activities, NACE Rev.2, which is comparable to the Ethiopian manufacturing sector two-digit classification, and classify the industries into Low, Middle, and High technology sectors. However, the Ethiopian manufacturing sector does not have industries that are categorized as high-tech industries in the European statistical classification. Firms grouped as medium-tech industries in the European statistical classification are, therefore, grouped as high-tech industries in our classification.

None of the IV estimations of equation (1) by government policy focus and tech-group meet the endogeneity assumption of the regressors, FDI, and competition. Table 1.9, therefore, presents the result based on fixed effect estimation. Column (1) shows the benchmark result based on the IV estimation for all domestic firms. Column(2) shows the result for domestic firms that belong to priority industries and account for 41% of the domestic firms. The coefficient estimate of FDI is positive and significant at a 10% significant level suggesting the presence of technology spillover to domestic firms that belong to the priority industries. A 1% increase in the sectoral level FDI in the priority sector increases a firm's productivity by 1.2%. Though the prevalence of the positive knowledge transfer of FDI in the priority sectors corroborates the policy focus on these industries by the Government of Ethiopia to achieve industrial development, the small magnitude suggests there is still more to be done.

The result also shows that the technology spillover effect of FDI in other sectors is negative and significant at a 10% significance level. This suggests the need for policy attention for the other industries as well to achieve all-round industrial development not focused only on a few industries. Unlike for the sample of all domestic firms, the negative competition effect of FDI is absent for the priority sector. This could be due to the huge demand for priority sector products filling the gap in the country by imports or the new FDI firms are focused on the international market. Column (4) of Table 1.9 shows the result for the high-tech firms while Column (5) is for low-tech firms. The result indicates that FDI has neither a technology spillover nor a product rivalry effect on either high or low-tech manufacturing firms in Ethiopia.

## 1.8 Conclusion

Many countries allocate a large amount of resources to attract FDI, In developing countries, FDI helps to overcome the investment gap, generate employment opportunities, and export earnings. In addition, it is believed they generate positive technology spillovers to domestic firms. In contrast, the empirical evidence on the technology spillover effect of FDI particularly for developing countries is at best mixed and is often actually negative. The reasons put forward for this negative spillover effect of FDI include the market-stealing effect of foreign-invested firms, the lower absorption capacity of domestic firms, and the geographic distance of domestic firms from foreign-owned firms. Yet, competition is one of the mechanisms through which technology transfer can occur and does not necessarily lead to market loss and a decline in productivity.

This paper disentangles the competition effect from the technology spillover effect of FDI by constructing product closeness and product market spillover indicators. These measures assign firms in the product market space and capture the competition pressure that firms face in the same or related product market (group). The result from the instrumental variable estimation technique using the 2013 – 2017 Ethiopian LMSMI from CSA reveals the presence of both horizontal technology transfer and product market spillover to domestic manufacturing firms.

The results suggest that the presence of FDI in a sector helps domestic firms to increase their productivity through technology transfer in the same two-digit sector where foreign firms are competing in related but not the same product groups. This positive knowledge spillover, however, is canceled out by the negative competition effect of FDI in the sector where firms are competing in the same product groups. The positive technology spillover of FDI is however far larger than the negative competition spillover of FDI indicating the importance of FDI in increasing the productivity of domestic manufacturing firms in Ethiopia. The economic significance of the estimates is, however, very small given the overall manufacturing industry productivity growth observed over the study period. This suggests the need for a concerted effort on the part of policymakers to achieve a higher level of technology transfer that would help to achieve the industrial development strategy of the country.

The result is robust to alternative productivity and product market competition measures. One particular interest in the robustness analysis is the robustness of the result to the sample of domestic firms that belong to the industries that are designated as priority industries by the Government of Ethiopia. The result shows the prevalence of knowledge transfer from FDI in domestic firms in the priority sector, but the magnitude is smaller than the whole sample of domestic firms. Although this finding supports the government's industrial development policy strategy, it also suggests the need for a coordinated effort to increase this technology spillover. The finding is important not only for Ethiopia but also for other Sub-Saharan African countries. They can look to Ethiopia's industrial development strategy as a model for knowledge transfer for boosting productivity and the contribution of the manufacturing sector to economic growth in the continent.

The study focuses solely on separating the competition from the intra-industry technology spillover. Therefore, further investigation of both backward and forward technology transfer of FDI is important to establish more persuasive evidence on the overall spillover effect of FDI in Ethiopia. As suggested by Abebe et al. (2022) it would also be important to look at the cost of attracting FDI; and to investigate the cost of resource misallocation due to a particular emphasis on priority sectors that are believed to have low technological sophistication using supplementary administrative data.

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# Appendix A

# Tables and Figures

Table A.1: Number of foreign and domestic firms by region over the years

| | Year | | | | | |
|---|---|---|---|---|---|---|
| Region | Firm ownership | 2013 | 2014 | 2015 | 2016 | 2017 |
| | 2013 | 2014 | 2015 | 2016 | 2017 | |
| Tigray | Domestic | 105 | 130 | 115 | 151 | 177 |
| | Foreign | 0 | 0 | 3 | 0 | 0 |
| Afar | Domestic | 7 | 7 | 5 | 3 | 11 |
| | Foreign | 0 | 0 | 0 | 0 | 2 |
| Amhara | Domestic | 153 | 178 | 180 | 201 | 243 |
| | Foreign | 4 | 4 | 6 | 4 | 11 |
| Oromia | Domestic | 308 | 352 | 395 | 417 | 466 |
| | Foreign | 46 | 52 | 54 | 27 | 37 |
| Somali | Domestic | 17 | 20 | 16 | 15 | 20 |
| | Foreign | 0 | 0 | 0 | 0 | 0 |
| Benishangul | Domestic | 3 | 2 | 3 | 4 | 3 |
| | Foreign | 0 | 0 | 0 | 0 | 0 |
| S.N.N.P | Domestic | 123 | 157 | 152 | 236 | 233 |
| | Foreign | 0 | 2 | 1 | 0 | 1 |
| Gambela | Domestic | 1 | 0 | 0 | 0 | 0 |
| | Foreign | 0 | 1 | 0 | 0 | 0 |
| Harari | Domestic | 13 | 16 | 16 | 16 | 26 |
| | Foreign | 0 | 0 | 0 | 0 | 1 |
| Addis Ababa | Domestic | 307 | 307 | 417 | 660 | 697 |
| | Foreign | 24 | 35 | 22 | 25 | 35 |
| DireDawa | Domestic | 37 | 48 | 43 | 75 | 72 |
| | Foreign | 0 | 2 | 2 | 1 | 3 |
| | Total Domestic FIRMS | 1,074 | 1,217 | 1,342 | 1,778 | 1,948 |
| | Total Foreign Firms | 74 | 96 | 88 | 57 | 90 |
| | Total Firms | 1,148 | 1,313 | 1,430 | 1,835 | 2,038 |

*Notes:* A firm is defined as a foreign firm if it has a foreign capital share in its total paid-up capital

Table A.2: The correlation coefficient of the variables

| | log(TFP) | Sectoral FDI | Competition | Export intensity | Frim size | Capacity utilization | Herfindahl index |
|---|---|---|---|---|---|---|---|
| log(TFP) | 1.00 | | | | | | |
| FDI | -0.08 | 1.00 | | | | | |
| FDIComp | 0.09 | 0.21 | 1.00 | | | | |
| Export intensity | -0.06 | -0.00 | -0.01 | 1.00 | | | |
| Frim size | 0.39 | -0.05 | 0.04 | 0.00 | 1.00 | | |
| Capacity utilization | -0.01 | 0.03 | -0.03 | 0.01 | 0.02 | 1.00 | |
| Herfindahl index | 0.00 | -0.08 | 0.03 | 0.06 | -0.20 | -0.03 | 1.00 |

Table A.3: Random effect vs fixed effect comparison: Hausman test

| | Whole sample | | | Domestic firms | | |
|---|---|---|---|---|---|---|
| | (1) RE | (2) FE | (3) RE (clustred SE) | (4) RE | (5) FE | (6) RE (clustred SE) |
| FDI | -0.002 | -0.001 | -0.002 | -0.002 | -0.000 | -0.002 |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.003) | (0.003) |
| FDIComp | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Export intensity | -0.075*** | -0.061*** | -0.075*** | -0.243** | -0.229* | -0.243** |
| | (0.014) | (0.017) | (0.004) | (0.112) | (0.138) | (0.104) |
| Firm size | 1.257*** | 1.281*** | 1.257*** | 1.254*** | 1.287*** | 1.254*** |
| | (0.036) | (0.045) | (0.036) | (0.037) | (0.046) | (0.037) |
| Capacity utilization | -0.000 | 0.002 | -0.000 | -0.001 | 0.001 | -0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) |
| Herfindahl index | 0.633*** | 0.706** | 0.633*** | 0.662*** | 0.841*** | 0.662*** |
| | (0.231) | (0.276) | (0.237) | (0.236) | (0.287) | (0.238) |
| Observations | 7764 | 7764 | 7764 | 7359 | 7359 | 7359 |
| Adjusted $R^2$ | - | -0.144 | - | | -0.174 | - |
| Hausman test (P-value) | - | 46.356(0.077) | - | 43.549 (0.126) | - | - |
| Overid test(P-value) | - | - | 65.478(0.001) | - | 1286.944(0.000) | - |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: First stage regression for Mahalanobis' distance measure

| | Mahalanobis | | FDI-Employment | | Addis Ababa | |
|---|---|---|---|---|---|---|
| | (1) FDI | (2) FDIComp | (3) FDI | (4) FDIComp | (5) FDI | (6) FDIComp |
| Exchange rate | -0.035*** | -0.133*** | -0.004*** | -0.289*** | -0.025*** | -0.668*** |
| | (0.002) | (0.014) | (0.002) | (0.043) | (0.004) | (0.132) |
| Weighted exchange rate | 0.000*** | 0.007*** | 0.000** | 0.003*** | 0.000*** | 0.006*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Relative fixed cost | -0.000 | 0.000 | -0.000** | 0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Export intensity | 0.719 | -0.966 | 0.832 | -5.315 | 0.654 | -17.010 |
| | (0.617) | (2.177) | (0.514) | (11.052) | (0.895) | (15.011) |
| Frim size | 0.680** | 2.364* | 0.690*** | 8.838** | 1.068*** | 10.909 |
| | (0.274) | (1.433) | (0.179) | (4.106) | (0.380) | (10.065) |
| Capacity utilization | -0.008 | -0.034 | -0.006 | -0.064 | 0.000 | 0.110 |
| | (0.013) | (0.054) | (0.011) | (0.140) | (0.014) | (0.155) |
| Herfindahl index | -13.074*** | -63.658*** | 1.328 | 79.545* | -2.601 | -256.452*** |
| | (1.893) | (11.371) | (1.189) | (44.208) | (2.446) | (69.811) |
| Observations | 7359 | 7359 | 7359 | 7359 | 4326 | 4326 |
| Adjusted $R^2$ | 0.578 | 0.415 | 0.514 | 0.417 | 0.577 | 0.353 |
| $R^2 within$ | 0.580 | 0.418 | 0.516 | 0.420 | 0.579 | 0.358 |
| F-stat | 76.138 | 158.742 | 4.794 | 153.652 | 10.599 | 63.165 |

N.B.: The first stage regression is estimated using fixed effect and includes year, region, and sector dummies. Clustered standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Classification of sectors into two technology groups

| ISIC Number | Low-Tech Sector | ISIC Number | High-Tech Sector |
|---|---|---|---|
| 15 | Food products and beverages | 24 | Chemicals and chemical products |
| 17 | Textiles | 25 | Rubber and plastics |
| 18 | Wearing apparel; dressing and dyeing | 26 | Other non-metallic mineral p |
| 19 | Tanning and dressing of leather | 27 | Basic metals |
| 22 | Publishing and printing | 30-33 | Office, computing, electrical products |
| 36 | Furniture; | | |

*Note*: This classification is based on the European statistical classification of economic activities, NACE Rev.2, which is comparable to the Ethiopian manufacturing sector two two-digit classification.

# Chapter 2

# Foreign direct investment and wage inequality in the Ethiopian manufacturing industry.

**Abstract:**

Foreign direct investment (FDI) in developing countries is often associated with skill upgrading and rising wage inequality. This paper provides micro-level evidence of the effect of FDI on wage inequality in a developing country that recently joined the global value chain in the footloose manufacturing industry. Using firm-level data for the Ethiopian manufacturing industry from 2013 to 2017, the study finds that despite the rise in wage inequality, the industry did not experience skill-biased technological change (SBTC) over the period. The two-stage system-GMM estimates of the translog cost function indicate that a 10% increase in the firm's foreign capital increases the share of skilled labor wages by 1.3 percentage points. FDI also increases firms' relative demand for skilled labor, driving the increase in wage inequality in the industry. These findings suggest that while SBTC is underway at the firm level in the Ethiopian manufacturing industry, it yet to be translated to the industry level.

*Keywords: FDI, skilled labor demand, wage inequity, Ethiopia*

*JEL Classification: F14; F23*

## 2.1 Introduction

Foreign direct investment (FDI) is expected to augment developing countries' limited investment, research, and innovation capability and boost economic growth. Many developing countries have implemented policies that promote FDI to create jobs, generate foreign currency, transfer knowledge, achieve technological change, and promote industrial development. Technological change can also affect labor market outcomes and contribute to wage inequality by shifting labor demand from the least skilled workers to highly skilled workers (Acemoglu 2002, Goldin & Katz 2010). However, much of the empirical research on this issue has focused on developed countries (Driffield 1996, Conyon et al. 2002), Latin American (Feenstra & Hanson 1997), or Asian countries (Chen et al. 2011, Lee & Wie 2015) that have a long history of trade liberalization and attracting FDI. Yet, the nature of FDI flowing to these countries, as well as their institutional, labor market characteristics, and administrative capacity, differ from those of many African countries, like Ethiopia, which have recently joined the global manufacturing value chain.

The generalizability of findings and applicability of policy recommendations from previous research to other developing countries is thus questionable and requires further investigation. This research aims to address this gap by examining the role of firm-level FDI (technology adoption) in explaining wage inequality in the Ethiopian manufacturing industry. The use of FDI as a source of alternative investment and employment opportunities in Ethiopia dates back to the 1940s (Gebreeyesus et al. 2017). For many years, Ethiopia had a command economy that discouraged private investment, including foreign investment. However, in the early 1990s, the country introduced a new political and economic system that promoted economic liberalization. This included privatizing state-owned enterprises (SOEs), including those that could be owned by foreigners. In 2002, Ethiopia launched a comprehensive industrial development policy to create an export-oriented manufacturing sector that supports the development of a skilled workforce and productivity. The 2012 Investment Proclamation emphasized FDI as a key driver of industrial development and provided various fiscal and financial incentives. As a result, Ethiopia has experienced significant growth in manufacturing sector FDI inflows. Oqubay

(2018) indicates that manufacturing FDI between 2012 and 2016 increased from around 1 billion USD to 3.5 billion USD. This inflow of FDI and the expansion of the manufacturing sector have made Ethiopia a new FDI hub in Africa.

The impact of FDI on skill-biased technological change (SBTC) and wage inequality may depend on the type of FDI and the labor market characteristics of the host country. Ethiopia's labor market is characterized by low labor costs, which may attract foreign firms. In today's globalized production, labor costs are critical to multinational firms' location decisions. With the rise in labor costs in Asia, Gelb et al. (2017) suggested that lower labor costs in Ethiopia could attract industries seeking to compete based on low wages. The flow of FDI into Ethiopia is thus likely to be related to the international competitiveness of local production due to low labor costs.

Moreover, Ethiopia's industrial policy and the resulting FDI inflows into the manufacturing sector are focused on light manufacturing industries that are unskilled labor-intensive. In these industries, foreign firms may not necessarily pay higher wages to attract skilled labor or retain their most productive workers. Oya & Schaefer (2019) also shows the centralized recruitment process in Industrial Parks (IP) where most foreign firms are located restricted wage competition among firms, and kept wages low. In this process, employees could not directly apply for jobs with individual foreign firms but rather had to go through the recruitment system shared by all firms.[1]

The combination of Ethiopia's labor market structure, the government's focus on unskilled labor-intensive manufacturing, and the nature of FDI inflows raises important policy questions: Has the Ethiopian manufacturing industry experienced SBTC over the study period? Does FDI lead to skill-biased technological change and wage inequality in Ethiopian manufacturing firms? We answer these questions by estimating the translog cost function and using the 2013-2017 Ethiopian Large and Medium-Scale Manufacturing Industry (LMSMI) panel data collected by the Ethiopian Central Statistical Service (CSS). The LMSMI is a census of all manufacturing firms with ten or more employees. We find that foreign firms pay higher wages for skilled labor than domestic firms, while they

[1] In addition, there is a tacit agreement among foreign firms not to employ individuals working in other factories in the same IP, which may perpetuate the situation of low wages.

employ a smaller share of skilled workers. Wage inequality began to increase in 2015, while the share of skilled labor employment declined. The lack of a simultaneous increase in the share of skilled labor with wage inequality confirms the absence of SBTC in the Ethiopian manufacturing industry over the period.

The two-stage system-GMM estimates indicate that an increase in the firm's share of foreign capital increases its share of skilled labor wages, while an increase in exports (another measure of technology adoption) reduces the share. A 10% increase in the firm's foreign capital increased the share of skilled labor wages by 0.002%. The result is robust to the change in the definition of FDI and the sample. The proportion of skilled labor share regression also shows that FDI increases the relative demand for skilled labor within firms in the Ethiopian manufacturing industry, indicating that within-firm SBTC is underway and driving wage inequality. These findings provide support to the skill-upgrading effect of technology adoption through FDI in developing countries like Ethiopia although the effect is very small compared to other developing countries. International trade (imports and exports) used as an alternative measure of technology adoption, however, does not explain the increase in the relative demand for skilled labor.

This paper contributes to the income distribution literature in two ways. Previous studies on SBTC and wage inequality focused on industry-level analysis (See, Feenstra & Hanson 1997, Lee & Wie 2015). Industry-level analysis, nonetheless, disregards firms' heterogeneity within the industry and may mask the wage inequality or the change in skilled labor upgrading happening within firms Pavcnik (2003). This paper contributes to this literature by looking at intra-firm wage inequality and skill upgrading. The results show that an increase in FDI explains the rise in the relative demand for skilled labor and drives wage inequality. The result conflicts with what Pavcnik (2003) find for Chilean manufacturing firms, and Doms et al. (1997) for the USA, i.e.; that technology adoption is not related to skilled labor employment. Second, the paper also adds to the literature by focusing on the least developing country, Ethiopia, which has joined the global manufacturing value chain recently. Moreover, the paper considers the persistence of skilled labor wage share in our estimation strategy and estimates a dynamic model. Failure to account for the persistent effect of skilled labor wage share within a firm underestimates the effect of FDI.

This paper is structured as follows: Section 2 reviews the literature on FDI and wage inequality. Section 3 describes the data source. Section 4 discusses the development of wage inequality and changes in skilled labor wages and demand by firm ownership type. Section 5 presents the model specification and estimation strategy. Section 6 analyzes the relationship between FDI and wage inequality. Section 7 concludes.

## 2.2 Literature review

Different theoretical models explain the role of technology adoption through FDI and international trade in affecting labor market outcomes. However, the theoretical prediction of whether foreign firms' presence exacerbates wage inequality is far from conclusive. Focusing on country-level effects and based on the general equilibrium model with comparative advantage, Feenstra & Hanson (1997) shows that FDI raises the skill premium in both developed and developing regions. Markusen & Venables (1998) include foreign firms' unique features into the general equilibrium model and show that the effect of the presence of foreign firms on unskilled labor in the host country can be either positive or negative. Incorporating the firm-specific nature of FDI and the presence of labor unions in the bargaining process, Zhao (1998) provides a formal treatment of the effect of FDI on wages and employment and shows that FDI benefits those workers with greater bargaining power and relatively in short supply.

Technology adoption through international trade can also affect wage inequality. The recent international trade model suggested that exporting increases the skilled labor demand and wages. Verhoogen (2008) model explains that exporting allows for quality upgrading, which is costly and requires more intensive use of higher-wage skilled labor. According to Matsuyama (2007) skilled-bias globalization model, international trade activities such as marketing and commercialization, transportation, and distribution require relatively skilled workers, resulting in a rise in wage inequality. The endogenous technological change model of Acemoglu (2003) shows that technological change in developing countries may take the form of embodied technology diffusion through increased imports of capital goods that are complementary to skilled labor.

The empirical literature on the role of FDI and international trade as a source of technological change and labor market outcomes in developed and developing countries is abundant. Studies in developed and emerging countries documented that a rise in demand for skilled labor is associated with technological changes (see, Autor et al. 2008, Katz & Murphy 1992, Machin & Van Reenen 1998) and corroborate the wage inequality effect of technological change. Card & DiNardo (2002), on the other hand, claim that wage inequality in the 1980s and 1990s in the United States is better explained by minimum wage regulation and labor union membership and thus cast doubt on the skill-biased technological change hypothesis. Others associate an increase in wage inequality in the United States with a decline in union membership (Western & Rosenfeld 2011) and a decline in the real value of the federal minimum wage (Lee 1999).

Empirical works on the effect of technological change on employment and inequality in developing countries are also numerous but mainly focused on the role of international trade. Harrison & Hanson (1999) find that within each Mexican industry, firms that import machinery and materials are more likely to employ a higher share of skilled workers than firms that do not import these inputs. After controlling for time-invariant plant level features, Pavcnik (2003) indicates the increased demand for skilled labor by Chilean plants in the early 1980s cannot be explained by the usage of imported materials. Yet, Raveh & Reshef (2016) indicates that capital import has a composition effect in developing countries in that imports of R&D-intensive capital equipment raise the skill premium while imports of less innovative equipment lower it.

Brambilla et al. (2012), using individual employment and wage data from sixteen Latin American economies, find that exports are positively correlated with the skill premium. Goldberg & Pavcnik (2007) have shown that most developing countries have experienced increased inequality with globalization measured using FDI or share of import/export in GDP. FDI also takes its share in the literature in both developed and developing countries in affecting skilled labor demand and wage inequality. In the United Kingdom, for instance, Driffield (1996) shows that foreign firms pay an average of around 7% higher wages while Conyon et al. (2002) indicate foreign firms pay 3.5% wages above the industry average. They attribute this difference partly to the higher productivity of foreign firms. In their cross-country analysis, Figini & Görg (2011) show that inward FDI stocks increase wage inequality in developing countries.

A large body of literature also investigated the role of FDI in wage inequality in many developing countries. Lee & Wie (2015) find that the spread of technologies through FDI caused demand to shift toward more skilled labor and increased wage inequality in the Indonesian manufacturing industry. Feenstra & Hanson (1997) also associates FDI with skill upgrading within industries in Mexico. Using firm-level data and ownership type, Chen et al. (2011) find that exposure to foreign investment increases inter-enterprise wage inequality in Chinese manufacturing firms. Controlling for unobserved plant characteristics for Chilean manufacturing firms, Pavcnik (2003) shows that the positive relationship between skill upgrading and different measures of FDI disappears. Likewise, Doms et al. (1997) find no association between the adoption of new technology and skill upgrading for US plants after controlling for unobserved plant features. Nonetheless, studies focused on these issues in the least developing countries that have become the major recipients of FDI in recent years such as Ethiopia are rare.

Though not focused on the manufacturing industry, Vargas Da Cruz et al. (2018) find that the number of approved (both implemented and not implemented) FDI projects are related to the employment of and higher wages for unskilled workers in Ethiopia. This, finding, however, could overestimate the effect of FDI since it includes greenfield FDI projects that did not materialize, and overlooked the possibility of technology upgrading from the actual investment which can be related to wage inequality. Haile et al. (2017), focusing on manufacturing firms for the period 1996-2004, find that firms with a higher share of foreign capital employ more skilled workers: and interpret the result as the skill-bias effect of FDI. In addition to ignoring current FDI inflows, the analysis fails to indicate whether there was a shift in skilled labor demand or wage inequality in the industry that might be explained by FDI. Abebe et al. (2022) and Chapter 1 (n.d.) of this dissertation also focused on technology spillover and the competition effects of FDI. This study thus complements previous studies on skilled labor demand and wage inequality by investigating how technology adoption through FDI and international trade affects skill upgrading and wage inequality in Ethiopia controlling for firm characteristics.

## 2.3 Data source and description

We start our analysis by exploring whether there is an increase in wage inequality in the manufacturing industry. For this, we use the 2013 to 2017 Ethiopian Large and Medium Scale Manufacturing Industry (LMSMI) Survey data collected by the Ethiopian Central Statistical Service (CSS). The LMSMI is a census of all manufacturing firms that use power-driven machinery, and employ ten or more workers. The manufacturing survey distinguishes workers as paid and unpaid workers; seasonal and temporary workers; and permanent and contract workers. We use permanent and contract workers who are further classified as non-production and production workers. Non-production workers include administrative, technical employees; and clerical and office workers and are defined as skilled workers while production workers are considered as unskilled workers[2]. So, skilled (unskilled) labor is measured by the total number of employees in each skill group working in a firm. The survey also provides the total annual wage bill by worker type. The monthly average wage for skilled (unskilled) workers at each firm is thus obtained by dividing the monthly wage bill of each skill group by the average number of employees in that skill group per month.

In addition, the data contain different important information about firms that include the share of foreign equity in each firm in the form of paid-up capital by ownership type, capital investment, export, import, and the number of production and non-production workers and their wages. We use a firm's equity share to define FDI in two ways. First,

[2] Leamer (1994) pointed out that this approach is prone to the misclassification of skilled and unskilled labor. Kahn & Lim (1998), however, indicates that this definition of skilled and unskilled labor could do better than the education-based classification since it incorporates skills based on unobservables and shows that the approach provides similar econometric results with education-based classification. Many other empirical studies used a similar approach (eg., Berman et al. 1994, Feenstra & Hanson 1997, Lee & Wie 2015, Sachs et al. 1994) and proved to be effective in tracking employment and wages by skill category.

FDI is defined as the share of foreign capital in a firm's total paid-up capital, and second, as an indicator variable of whether a firm is a foreign firm or not. A firm with positive foreign capital is defined as foreign. The data for paid-up capital, output, capital, wage (for both skilled and unskilled workers), and export and imported materials are shown in local currency units, Birr, and deflated using the 2016 GDP deflator provided by World Development Indicators (WDI).

The problem with LMSME data is the lack of a unique panel identifier starting from 2012. We therefore use the panel identifiers constructed for the period 2013 – 2017 obtained from the Ethiopian Policy Research Institute (PSI), formerly known as the Ethiopian Development Research Institute. The panel is constructed based on the firm ISIC code, establishment number, taxpayer identification number, phone number, and establishment name. Diao et al. (2021) and Gebrewolde et al. (2022) used these panel identifiers to construct panel ID for their analysis. Using this panel identifier, we obtained an unbalanced panel of 3,609 firms that are observed for two or more years. These firms constitute 9,273 observations corresponding to 72% of the total observations in the five-year survey. Missing values for firm identifier and year, and other observations with inconsistent values are either excluded or imputed whenever possible. The final data are then winsorized for possible outliers at the $1^{st}$ and $99^{th}$ percentiles and comprise an unbalanced panel of 2,772 firms and a total of 6,190 firm-year observations. In this data, foreign firms account for 8.2% of manufacturing firms. This number is higher than the 6% reported in Diao et al. (2021) for the period between 1996- 2017. The rise in the proportion of foreign firms is expected given the increase in manufacturing FDI after 2012. Table 2.1 provides descriptive statistics.

## 2.4 Descriptive analysis

This section analyzes whether or not SBTC is present in the Ethiopian manufacturing industry. We start our analysis by documenting the trend in wage inequality. Because of the lack of data on matched individual-level wages and education level, we focus on a single indicator to measure wage inequality. Figure 2.1 presents the log wage of both the

Table 2.1: Summary statistics

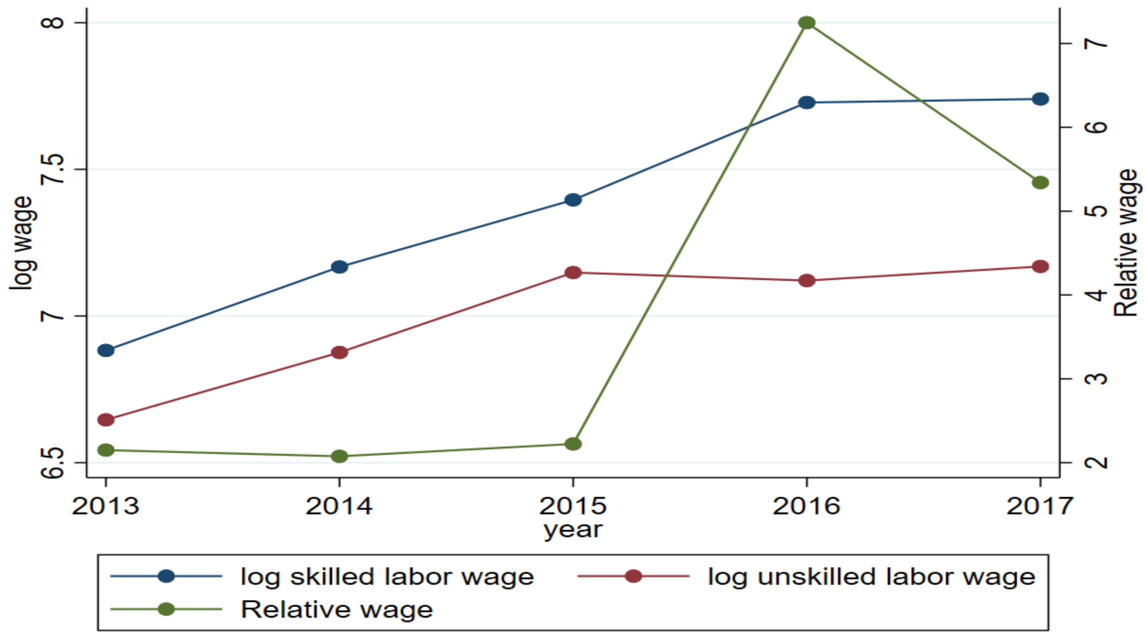
| | Mean | SD | Min | Max | Observations |
|---|---|---|---|---|---|
| Share | 0.37 | 0 | 0.00 | 1.00 | 6190 |
| Capital | 21.28 | 61 | 0.00 | 435.69 | 6190 |
| Output | 53.34 | 136 | 0.05 | 921.08 | 6190 |
| Export | 0.03 | 0 | 0.00 | 1.00 | 6190 |
| Import | 0.39 | 0 | 0.00 | 1.00 | 6190 |
| FDI | 5.38 | 21 | 0.00 | 100.00 | 6190 |
| Foreign | 0.07 | 0 | 0.00 | 1.00 | 6190 |
| Relative wage | 4.18 | 13 | 0.11 | 107.73 | 6190 |
| Skilled worker | 30.24 | 65 | 1.00 | 417.00 | 6190 |
| Unskilled worker | 69.87 | 140 | 1.00 | 920.00 | 6190 |
| Skill labor proportion | 0.30 | 0 | 0.02 | 0.83 | 6190 |

N.B.: Capital and Output are in thousands of 2016 prices. Skilled and unskilled labor are measured by the number of employees. Firms with zero wages for skilled labor are included as long as they are observed for at least two years.

average skilled and unskilled labor wage and their ratio: relative to wage-skill premium. The log wage of skilled labor shows a modest rise between 2013 and 2017 while unskilled labor wages followed the same trend until 2015 then declined. The gap between skilled and unskilled wages started to emerge in 2015. Over the years 2013 to 2017, Ethiopian manufacturing firms experienced an increase in the relative wage by 60%

The rise in wage inequality in the manufacturing industry could be attributed to various market and non-market factors, and macroeconomic developments. The first possible reason is the exogenous shock from the public sector wage increase in 2014/15. The government of Ethiopia adjusted the nominal wages for public servants to overcome the erosion in the value of real wages due to high rates of inflation observed in the past. This could have a proportional spillover effect on private and manufacturing sector wages for both skilled and unskilled labor. Moreover, looking at the inflation rate over the study period indicates that average annual inflation was 8.4%. Thus, inflation should have kept the real wages of both skilled and unskilled workers stable while having an indeterminate effect on the relative demand for skilled workers. Figure 2.1, however, demonstrates that until 2015, both skilled and unskilled workers' log real wages increased proportionally, but this trend changed after 2015 when the skilled labor wage rose while those of unskilled workers almost remained constant.

Figure 2.1: Real wage by labor type and relative wage.




Source: Own calculation based on the 2013-2017 LMMIS data.

Another plausible argument for the rise in wage inequality is a skill-biased technological development that could be expressed by the increase in demand for skilled labor despite the rise in wages. Figure 2.2 shows the average proportion of skilled labor at the firm level over the study period. In the face of the increasing relative wage, the skill labor demand, represented by the proportion of skilled labor, declined from 32.5% in 2013 to 28.7% in 2017. The absence of a simultaneous rise in relative wage and skilled labor demand confirms the lack of skill-biased technological change over the study period, and it is in conflict with is found in other developing countries such as Colombia (Attanasio et al. 2004); Chile (Pavcnik 2003) and Indonesia (Lee & Wie 2015) during the period of rapid trade liberalization and technology adoption through FDI.

The decline in skilled labor demand at the industry level could be associated with two possible factors. The first is the characteristics of the labor market. Over the years 2013 to

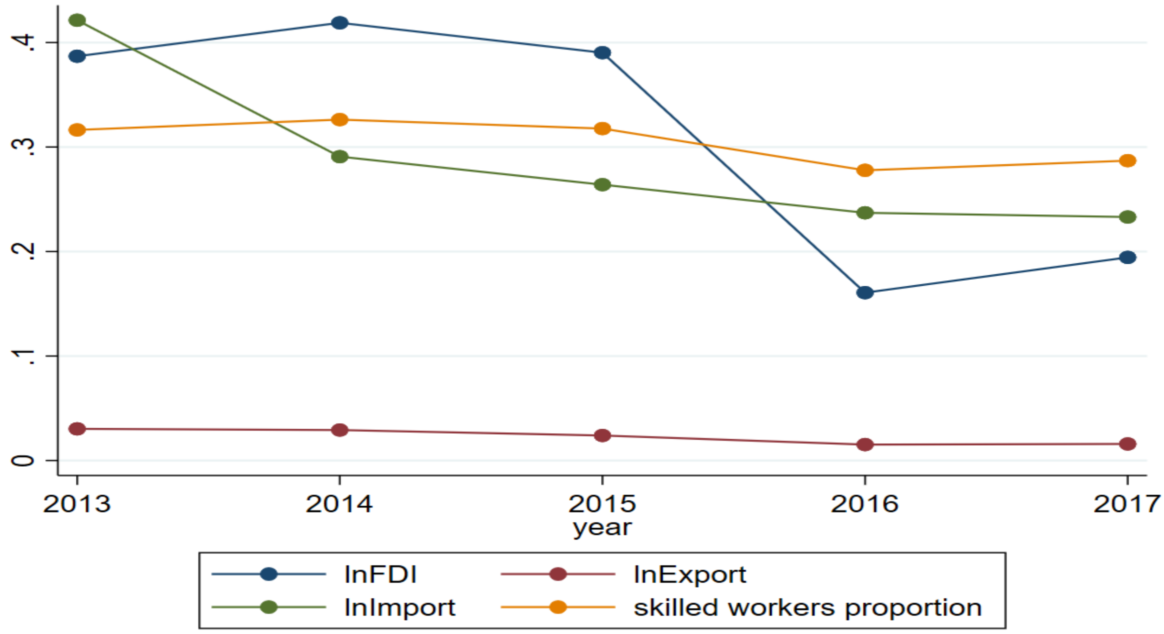
2017, Ethiopia experienced real GDP growth of 10.3%. Though this growth is believed to have contributed to the decline in unemployment, it remains the most prominent feature of the urban labor market with an unemployment rate of 19.1% in 2018. The prevalence of high unemployment provides the country a competitive advantage to attract FDI because of lower labor costs per worker. One major reason for the current inflow of FDI could thus be related to this low-cost advantage. In such an environment, most FDI flow could be on the low-skilled labor-intensive sectors. The data show that around 47% of foreign firms which account for 8.3% of the manufacturing sector employment are in low-skilled labor-intensive light manufacturing industries.[3] On the other hand, foreign firms in the relatively skilled labor-intensive sectors employ 4.9% of the workforce. This is consistent with the 2016 World Bank report on the labor market which confirms that the manufacturing industry in Ethiopia remains more crucial for unskilled labor. Expansion of a firm's operations may not necessarily entail an increase in the proportion of skilled labor within a firm since very few skilled workers in some key positions are required to run unskilled labor-intensive firms.

The second possible factor is the political upheavals that erupted in the final two years of the study period. The 2014-2016 "Oromo Protest"[4] that spread to the Amhara region as the "Amhara Resistance struggle" in 2016 caused the destruction of private properties including manufacturing firms and led to the suspension of operations by some firms including foreign firms. Following this political instability, the number of foreign firms declined by 23/% from 74 in 2014 to 57 in 2016 while the number of domestic firms increased. The change in the number of foreign firms was, however, different across regions. In the Oromia region, which encompasses the surrounding Addis Ababa, Ethiopia's capital city, and has long been the hub of manufacturing firms, foreign firms declined by 40%. (See, Table B.2). Addis Ababa also shows a similar decline while the Amhara region, which was considered relatively safe for FDI during the same period, on the contrary, witnessed

[3] We adopt a similar approach implemented in Chapter 1 (n.d.) to classify the manufacturing sector into low-skilled labor-intensive and relatively skilled labor-intensive industries and these sectors are presented in Table B.1.

[4] In 2014, Ethiopia witnessed the largest and most devastating protest against the government. This protest included the destruction of private properties including manufacturing firms in Oromia and Amhara regions.

Figure 2.2: Proportion of skilled labor and technology use.



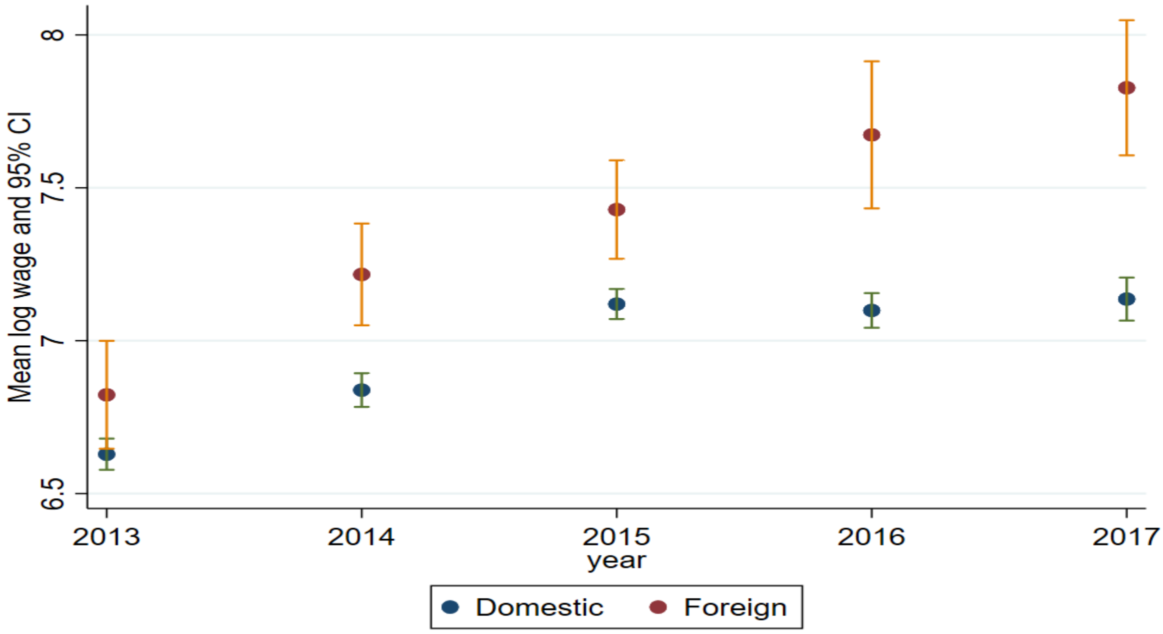

Source: Own calculation based on the 2013-2017 LMSME Survey data.

a modest rise. The use of foreign technology by firms measured in the FDI, imports, and exports also declined over the years (see, Table B.2 and Table B.3). However, business shutdown and the resulting change in sample composition may not necessarily explain the observed decline in the proportion of skilled labor as both the employment of skilled and unskilled labor is expected to decline. A simple graphical examination of the trend for the proportion of skilled labor for the balanced panel (see, Figure B.1) indicates the same declining trend though the rate is different.[5] Moreover, as indicated in the 2016 World Bank report on the labor market, it should be noted that the manufacturing industry in Ethiopia remains more important for unskilled labor.

A comparison of skilled labor employment and wages by firm ownership shows that foreign firms pay higher wages to skilled workers, even though they employ a smaller share of skilled workers. This finding contradicts the common belief that foreign firms are more skill-intensive than domestic firms. However, it is consistent with the findings by Coniglio et al. (2015) that the jobs generated by foreign firms in Sub-Saharan Africa are relatively less skill-intensive compared to those generated by domestic firms. Figure 2.3 presents the

[5]The formal test of selection bias due to attrition in the firm-level skilled labor demand regression is presented in Table B.6 and it shows that there is no attrition effect.

Figure 2.3: Log wage of skilled labor by firm ownership type.



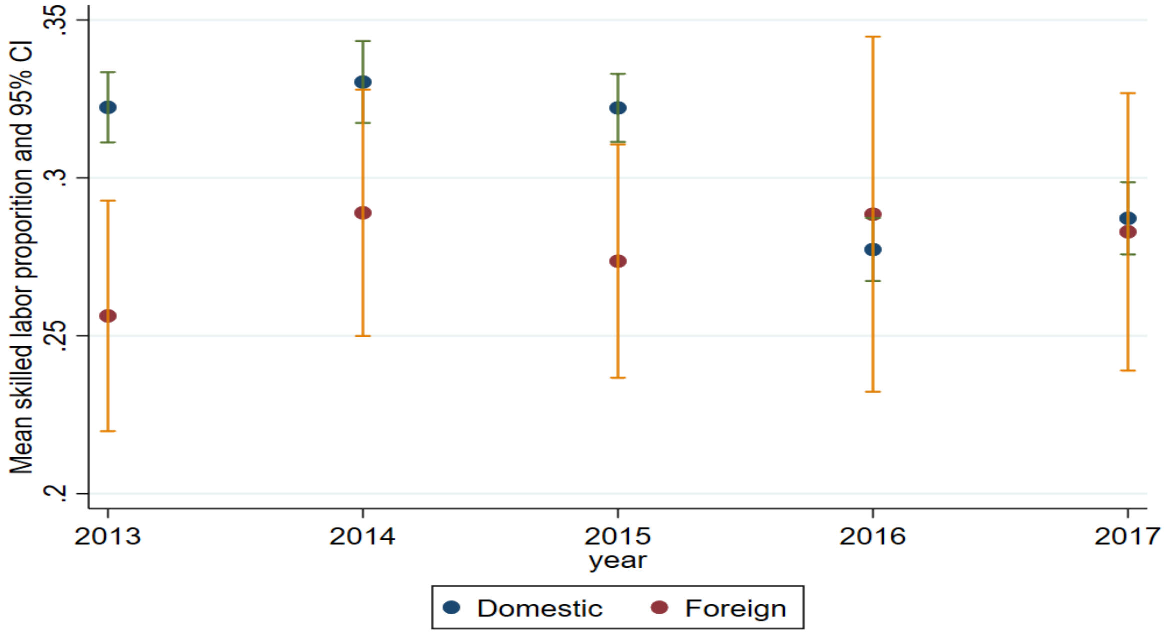

Source: Own calculation based on the 2013-2017 LMSME Survey data.

mean log wage of skilled labor for domestic and foreign-owned firms and the estimated 95% confidence interval over the years 2013 to 2017. The result indicates that on average foreign firms pay higher wage rates for skilled labor than their domestic counterpart in the Ethiopian manufacturing industry. This result is obtained despite the centralized recruitment process that restricted wage competition between firms in industrial zones (See, Oya & Schaefer 2019), where most new foreign firms are located. The difference in the mean wage between domestic and foreign firms has also gotten wider in the last two years.[6]

Figure 2.3, shows that domestic firms employ a higher proportion of skilled labor than foreign firms, although the gap has narrowed in recent years. This could be because foreign firms are larger and employ more production workers than non-production workers. Our data support this claim: foreign firms employ an average of 47.5 skilled workers, compared to 25 for domestic firms. Foreign firms also employ a disproportionately large number of unskilled workers, with 147 compared to 57 for domestic firms. On average, domestic

[6]We check whether there is a difference in the sectoral composition of domestic and foreign firms that can be reflected in higher skilled labor wages in sectors where most foreign firms are present. Foreign firms are present in almost all sectors and pay higher wages in sectors except in the textile, and paper and paper related sectors (see, Table B.4).

Figure 2.4: Proportion of skilled labor by firm ownership type.




Source: Own calculation based on the 2013-2017 LMSME Survey data.

firms employ around 87.2 workers, while foreign firms employ 205.4.

The descriptive analysis shows that wage inequality is prevalent in the Ethiopian manufacturing industry while skill-biased technological change (SBTC) is absent. Wage inequality has risen despite declining FDI and falling skilled labor employment. The findings also show that foreign firms pay higher wages on average than domestic firms, even though domestic firms employ a higher proportion of skilled labor. Comparing mean wages between domestic and foreign firms gives us some insight into how the presence of foreign-invested firms affects wages in the manufacturing industry, however, it does not prove that FDI has caused wage inequality to rise. The next section presents a formal test of the relationship between wage inequality and firm-level technology adoption through FDI.

## 2.5 Model specification

The role of FDI in explaining wage inequality in the Ethiopian manufacturing industry is explored more formally using the restricted variable cost function of firm $i$ at time $t$

presented in equation (1) below:

$$TVC_{it} = (W_{sit}, W_{uit}, K_{it}, Y_{it}, T) \tag{2.1}$$

where $TVC_{it}$ is a total variable cost of firm $i$ at time $t$ measured as total labor costs; $(W_s(W_u))_{it}$; is the wage of skilled (unskilled) workers and measured as the monthly average wage of non-production (production) workers; $K_{it}$ is the stock of quasi-fixed firm capital stock; $Y_{it}$ is output, and $T$ is an index of technology and assumed as a function of time. Approximating equation (1) with translog equation following Berman et al. (1994) and applying Shephard's lemma to obtain the change in total variable cost with respect to the change in the price of skilled labor ($W_s$) gives the share of skilled labor in total wage bill expressed as:

$$Share_{it} = \beta_1 lnK_{it} + \beta_2 lnY_{it} + \beta_3 ln\left(\frac{W_s}{W_u}\right)_{it} + \beta_4 lnTec_{it} + \gamma_t + \delta_i + \epsilon_{it} \tag{2.2}$$

where $Share_{it}$ is the share of skilled labor wage in the total wage bill of firm $i$ at time $t$. It is expressed as a ratio and measures skill upgrading or relative demand for skilled labor. $K_{it}$ is quasi-fixed capital stock, $Y_{it}$ is output, and $W_{sit}$ and $W_{uit}$ are the wages of skilled and unskilled (production) workers. $\gamma_t$ is a set of year dummies that control for possible variation in the political and macroeconomic environment over the years while $\delta_i$ controls for time-invariant unobserved firm heterogeneity that could be correlated with the share of skilled labor wage. SBTC studies in many developing countries implement the same approach and use FDI as a proxy for technology (see, Doms et al. 1997, Lee & Wie 2015, Machin & Van Reenen 1998, Pavcnik 2003).

Such a specification implicitly assumes that FDI is the source of technology transfer and there is technological change when firms use foreign capital. The technology spillover literature in most developing countries, however, finds either a negative or negligible spillover effect on domestic firms (See, Aitken & Harrison 1999, Haddad & Harrison 1993, Lu et al. 2017). Though not firm-level data, Abebe et al. (2022) find that domestic manufacturing firms in Ethiopia benefit from foreign firms' presence in their district, and motivate them to upgrade their production process. Similarly, disentangling the pure technology effect of FDI in Ethiopia, in Chapter 1 (n.d.) we find that the presence of FDI in the same industry increases technology transfer to Ethiopian domestic manufacturing firms. Haile et al. (2017) find that firm-level FDI increases skilled labor employment in Ethiopia and interpreted the result as evidence of technology transfer.

We therefore use FDI as our measures of technology adoption at a firm level and include it in the translog cost function replacing the $Tec_{it}$. The model presented in Equation (2) is finally specified as follows:

$$Share_{it} = \beta_1 lnK_{it} + \beta_2 lnY_{it} + \beta_3 ln\left(\frac{W_s}{W_u}\right)_{it} + \beta_4 lnFDI_{it} + \gamma_t + \delta_i + \epsilon_{it} \tag{2.3}$$

This model specification takes into account the heterogeneous nature of firms within an industry using the firm fixed effect,$\delta_t$, and controls for the unobserved economy-wide shocks in the share of skilled labor wage using time dummies, $\gamma_t$. A positive $\beta_1$ coefficient indicates the existence of capital skill complementarity and reflects changes in the skill bias of technology embedded in the capital. If the coefficient on the output variable, $\beta_2$, is not significantly different from zero, the constant returns to scale hypothesis fails to be rejected. To control for possible technology adoption through international trade that may affect skilled labor employment and wage inequality, we include imports and exports. Firms lacking data on imports and exports were presumed not to trade internationally.

## 2.6 Estimation strategy and results

The SBTC literature shows that the relative wage variable in equation (2) could be endogenous and may suffer from division bias since the wage bill variable is also used to calculate the dependent variable (Berman et al. 1994). The literature has adopted different approaches to overcome these problems Berman et al. (2005) and Pavcnik (2003), for instance, removed relative wage from the model and took the risk of omitted variable bias, while Lee & Wie (2015) keep the variable because of significant cross-industry variation of the variable in their data. Harrison & Hanson (1999) used relative wage, instead of skilled labor wage share, as a dependent variable to overcome the problem that skilled labor wage share is both determined, and determined by relative wage and output. However, we decided to use the cost function; and keep relative wage in the model since the variable exhibits a significant variation across firms in the data and allowed for possible endogeneity of relative wage.

Though wage inequality models such as Acemoglu (2002) treated FDI as an exogenous shock, it is possible that multinationals "cherry-pick" productive domestic firms with high wage levels that may lead to a positive correlation between the two. The literature on wage inequality also indicates that capital and output could be endogenous. In our estimation strategy, we, therefore, allow for the endogeneity not just of the relative wage but also for capital, output, and FDI. Since quite some firms change sector and region over the years, we control for region, and sector dummies in addition to year dummies. To account for possible endogeneity generated by the flow of FDI to industries and regions over time, we include sector-year and region-year fixed effects. Another concern with firm-level analysis is the entry and exit of firms which may bias our estimate. The fact that we have unbalanced panel data suggests the presence of firm entry and exit which may bias the result due to selection bias. The test for selection bias using the missing lag indicators for firm entry or exist, however, confirms the absence of selection bias[7].

Most empirical evidence on wage inequality relies on OLS regression estimates based on four or five-year differenced equations at the industry or regional level (see, Berman et al. 2005, Feenstra & Hanson 1997, Lee & Wie 2015). Pavcnik (2003) and Chen et al. (2011) also use firm-level data and estimate their model using fixed effect. Yet, these studies do not consider the heterogeneous persistence of skilled labor composition and wage. We, therefore, use a two-stage system GMM estimator and control for the persistence effect of the dependent variable.

[7] Results for the effect of attrition using missing lag indicator are set out in Table B.6. The result indicates that the missing lag indicator is insignificant suggesting the absence of selection bias.

### 2.6.1 Empirical results from the static model

Results for the static model based on different estimation methods of equation (3), where the dependent variable is the share of the skilled labor wage bill, are presented in Table 2.2. Though we expect unobserved plant heterogeneity, we undertake both the Hausman and the correlated coefficient tests to compare the fixed effect and random effect estimation techniques. Both tests support the fixed-effect method. Column (1) of Table 2.2 presents the result from the fixed effect estimates of equation (3). The estimated coefficient of FDI is positive and statistically different from zero. Firms that have more foreign capital have a higher share of skilled wages in their total wage bill. The coefficient for capital is positive and statistically significant. The result indicates that holding other firm characteristics constant, firms that obtain additional capital pay higher wages for skilled workers suggesting the presence of capital and skilled labor complementarity in the Ethiopian manufacturing industry. The significant negative coefficient for output indicates that firms increasing their output decreases their wage bill share to skilled workers. This conflicts with the constant-returns hypothesis which implies that input shares are invariant to scale.

Column (2) reports the result from the same FE estimation from column (1), but it includes two additional measures of technology adoption, imports, and exports. With the addition of the two variables, the results remain the same. Yet, the estimated effect of exports on the share of skilled labor wage is negative. This conflicts with the Stolper–Samuelson theorem prediction that exports increase the price of skilled-intensive goods; and hence skilled labor wage. Notwithstanding, the negative result is not unlikely given that exporting firms in developing countries specialize in labor-intensive products that rely more on unskilled workers. Export data by sector from the National Bank of Ethiopia (NBE) support this argument. Over the last five years, 96.4% of Ethiopia's manufacturing exports were obtained from the unskilled labor-intensive sectors.[8] The result is also consistent with Di Gropello & Sakellariou (2010) and Lee & Wie (2015) findings for Indonesia, a developing country with more labor-intensive exports. The esti-

[8]Ethiopia's Manufacturing export data over the study period are presented in Table B.5.

mated coefficient for import is positive but remains insignificant in all specifications. The result is contrary to the positive effect of R&D intensive capital import on skill premium in developing countries by Raveh & Reshef (2016) and Lee & Wie (2015). The lack of significance could be related to the fact that import value captured in LMMIS data is only for raw material import, and it suggests raw material import of manufacturing firms doesn't affect wage inequality.

Table 2.2: Share of skilled labor wage regression from static model

| | FE | FE | FD | FD | FDGLS |
|---|---|---|---|---|---|
| ln(Capital) | 0.003* | 0.003* | 0.002 | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(Output) | -0.009** | -0.009** | -0.009* | -0.009* | -0.010** |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| ln(Relative wage) | 0.100** | 0.100*** | 0.073* | 0.073* | 0.076*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| ln(FDI) | 0.006* | 0.006* | 0.008* | 0.008* | 0.006 |
| | (0.004) | (0.003) | (0.004) | (0.004) | (0.046) |
| ln(Expor) | - | -0.083* | - | -0.095* | -0.100* |
| | | (0.046) | | (0.053) | (0.046) |
| ln(Import) | - | -0.008 | - | -0.008 | -0.001 |
| | | (0.014) | | (0.016) | (0.015) |
| Constant | 0.545*** | 0.545** | 0.007 | 0.008 | 0.002 |
| | (0.101) | (0.101) | (0.012) | (0.012) | (0.010) |
| Observations | 6,190 | 6,190 | 3,288 | 3,288 | 3,288 |
| Number of firms | 2,772 | 2,772 | 1,928 | 1,928 | 1,928 |
| R-squared | 0.139 | 0.176 | 0.121 | - | - |
| Year, region & sector dummy | Yes | Yes | Yes | Yes | Yes |
| Region*Year dummy | Yes | Yes | Yes | Yes | Yes |
| Sector*Year dummy | Yes | Yes | Yes | Yes | Yes |

*N.B.:* The regression results from fixed effect (FE) and first difference (FD) estimates and includes region and sector dummies in addition to year dummies since some firms change sector and region. The dependent variable is the share of skilled labor wage. FDI is measured as the share of foreign capital in the total paid-up capital of a firm. Robust standard errors are in parentheses and *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The FE estimation is efficient if idiosyncratic error terms are serially uncorrelated and the strict exogeneity assumption holds. To confirm the robustness of the result from the FE estimation, we estimate the same model using the First Difference (FD) estimation technique. The result from the FD estimation presented in Column (3) of Table 2.2 is almost similar to the FE estimation result, yet the significance of capital disappears while relative wage becomes significant at a higher significance level with lower magnitude. This may suggest the lack of the strict exogeneity assumption for some variables. The result for capital is consistent across the other specifications and may reflect the absence of capital and skill complementarity. The effect of FDI continues to be positive and significant. The significance of output also continues to hold with a relatively lower magnitude. The result remains the same even after the inclusions of import and export in Column (4) where the coefficient estimate of export is still negative and significant as indicated in Column (2) in the fixed effect estimation method.

The result from the FD estimation is, however, subject to specification tests. FD is preferable over fixed effect if the first differencing avoids the possibility of serial correlation in the idiosyncratic error term. Wooldridge (2010, Chapter 10.6.3) indicates that in the absence of serial correlation in the idiosyncratic error term, the first-differenced error should exhibit a first-order serial correlation of 0.5. We found that after computing the robust variance matrix for the FD estimator, the estimated correlation of the idiosyncratic error term is -0.43, which is marginally different from 0.5. The test for serial correlation for the differenced error term, nonetheless, indicates that the error term still exhibits a strong positive serial correlation with a p-value of 0.037[9] suggesting that the FD estimation method is not efficient.

If the strict exogeneity assumption holds and the serial correlation is not related to a dynamic data-generating process, we can use the FDGLS procedure to estimate the static model as it provides efficient estimates. To test the strict exogeneity assumption of the regressors in the first difference of equation (2) of the static model, we use the feedback effect approach as outlined in Wooldridge (2010, Chapter 10.7.1). The result reveals that no variables have feedback effects and confirms that the strict exogeneity assumption is not violated in the static model[10]. We thus estimate the model using the FDGLS estimation method, and column (5) of Table 2.2 presents the result of the FDGLS method and indicates that all variables have almost the same effect and magnitude as in

[9]The Wooldridge test for autocorrelation also shows the presence of first-order autocorrelation with a P-value of 0.008.

[10]The test of exogeneity results for the static model using the feedback effect is presented in Table B.7

the FD method presented in column (4). FDI has also a positive effect on a firm's share of skill labor wage bill, but it is marginally insignificant even at a 10% significance level with a p-value of 0.106.

The preceding analysis indicates the absence of capital and skilled labor complementarity in Ethiopian manufacturing firms. The result is consistent with the World Bank (2016) findings which indicate the importance of the manufacturing industry for unskilled workers. Though insignificant, the estimated positive relationship between FDI and the share of skilled workers' wage bill could be interpreted as firm-level technology adoption through FDI causing an increase of within-firm skill upgrading or it could be a simple rise in wage inequality. It is important to note that the descriptive analysis presented above indicates that the uptick in wage disparity occurred during a period when the manufacturing industry did not experience skilled biased technological progress. Consequently, it is difficult to interpret the positive correlation of FDI and the share of skilled labor wage as skill upgrading as others have done Ethiopia (see, Haile et al. 2017). Moreover, it is possible that the share of skilled labor wage can have persistence, and failure to account for this persistent effect may bias the estimate.

### 2.6.2 Empirical results from the dynamic model

The analysis so far is based on the static model presented in equation (3). The positive serial correlation of the differenced error term in the static model discussed above, however, could be related to a dynamic data-generating process with the lagged dependent variable as an explanatory variable. Moreover, Haltiwanger et al. (2007) show that firms' productivity, skill compositions, and wage payment exhibit heterogeneity and persistence. They attribute these heterogeneous persistent effects to the firm's factors and endowments such as technology, capital, and other unobserved characteristics. The failure to consider the persistence of skill labor wage share could potentially bias static model estimates and lead to erroneous conclusions and policy advice. We therefore estimate the dynamic model presented in equation(4) below using the system GMM method where capital, output, relative wage, and FDI are treated as endogenous variables.

$$Share_{it} = \alpha_1 Share_{it-1} + \beta_1 lnK_{it} + \beta_2 lnY_{it} + \beta_3 ln\left(\frac{W_s}{W_u}\right)_{it} + \beta_4 lnFDI_{it} + \gamma_t + \delta_i + \epsilon_{it} \tag{2.4}$$

The dynamic model is first estimated using the Arellano & Bond (1991) (AB) difference GMM method (dGMM) and then using the Arellano & Bover (1995) system GMM approach.[11] We treat the lag-dependent variable as a predetermined variable and allow capital and relative wage to be endogenous variables while the other variables are treated as strictly exogenous. We use the second and third lag of the lagged dependent as an instrument for the first differenced lagged dependent variable. The second and third lags of the endogenous variables are also used as instruments for the endogenous variables. For the strictly exogenous variables in the difference model, we use their first difference as instruments. To reduce the proliferation of instruments, we also collapse the instruments. Table 2.3 presents the result from the dynamic model. Columns (1) replicate the result from the static model reported in Table 2.2. Columns (2) and Columns (3) show the result from the first-stage and second-stage difference GMM estimators respectively. The estimated coefficient on the lag-dependent variable from these estimation techniques is insignificant and may indicate that the dynamic model specification is incorrect.

In a short period like ours, Blundell & Bond (1998) argues that the difference-GMM may suffer from weak instruments if the dependent variable follows near a random walk or the difference between cases is large relative to the difference within cases. Gørgens et al. (2019) also show that such an under-identification of the autoregressive parameter can arise even when the autoregressive parameter is less than 1. The estimates from difference-GMM could therefore be downward-biased. We use Arellano & Bover's (1995) and Blundell & Bond's (1998) system-GMM estimator, which augments the AB estimator by introducing additional moment conditions for the level model. System-GMM uses differenced instruments for the variables in level and assumes that these instruments are exogenous to the unobserved heterogeneous fixed effects. We used the first lag of the

[11] The dynamic model is estimated using kripfganz2019's (2019) ***xtdpdgmm*** Stata command.

first difference of the dependent variable, the first difference of the other endogenous variables, and the exogenous variable as an instrument for the level models in addition to the previous instruments discussed above for the difference equation.

Table 2.3: Share of skilled labor wage regression from dynamic model

| | (1) FDGLS | (2) dGMM1 | (3) dGMM2 | (4) sGMM1 | (5) sGMM2 | (6) sGMM2 |
|---|---|---|---|---|---|---|
| L.Share | - | -0.064 | -0.028 | 0.203*** | 0.207*** | 0.226*** |
| | | (0.279) | (0.263) | (0.051) | (0.053) | (0.049) |
| ln(Capital) | 0.002 | 0.060 | 0.088 | 0.002 | 0.002 | 0.002 |
| | (0.002) | (0.062) | (0.075) | (0.003) | (0.003) | (0.003) |
| ln(Output) | 0.010** | -0.003 | -0.027 | -0.017** | -0.016** | -0.018*** |
| | (0.005) | (0.063) | (0.074) | (0.007) | (0.007) | (0.006) |
| ln(Relative wage) | 0.076*** | 0.097 | 0.178 | 0.076*** | 0.077*** | 0.067*** |
| | (0.008) | (0.145) | (0.164) | (0.012) | (0.012) | (0.012) |
| ln(FDI) | 0.006 | -0.016 | -0.071 | 0.015** | 0.014* | 0.013* |
| | (0.004) | (0.109) | (0.113) | (0.007) | (0.007) | (0.007) |
| ln(Export) | -0.101** | 0.035 | 0.052 | -0.128* | -0.150** | -0.160** |
| | (0.046) | (0.180) | (0.170) | (0.071) | (0.073) | (0.079) |
| ln(Import) | -0.001 | 0.046 | 0.064 | -0.001 | -0.010 | 0.000 |
| | (0.015) | (0.073) | (0.085) | (0.026) | (0.026) | (0.025) |
| Observations | 3288 | 3288 | 3288 | 3288 | 3288 | 3578 |
| AB(1) | - | 0.103 | 0.056 | 0.000 | 0.000 | 0.000 |
| AB(2) | - | 0.634 | 0.921 | 0.616 | 0.636 | 0.861 |
| Hansen-J(P-value) | - | 0.068 | 0.561 | - | 0.296 | 0.661 |
| Difference-in-Hansen | - | - | - | - | 0.116 | 0.251 |

N.B.: "dGMM1" and dGMM2" respectively indicate the first difference and second difference GMM estimators while "sGMM1" and "sGMM2" refer to the one-stage and two-stage system GMM estimator respectively. All regression includes time, region, and sector dummies. The exogenous variables are Output, FDI, Import, and Export. The specification test statistics are the Arellano and Bond (AB) test for no serial correlation, the Hansen-J statistics for the validity of overidentifying restriction, and the Difference-in-Hansen test for the validity of additional overidentifying restrictions of the level equation. Standard errors robust to serial correlation and heteroskedasticity are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Columns (4) to (6) of Table 2.3 show the result from the first stage and two-stage system GMM estimation methods.[12] We first note that the estimated autoregressive coefficient is significant and suggests that a static model may not be appropriate due to the persistence of the skilled labor wage share such that system GMM provides a good

[12] To overcome the omitted variables problem, we include lags of the explanatory variables and compare the two models with and without lag of the explanatory variables estimated with two-stage system GMM method. The results based on the Andrews & Lu (2001) model and moment selection criteria indicate that the model without the lag of the explanatory variables, with lower values of the criteria, is preferred(see, Table B.8).

estimate of the true parameter.[13] The reliability of the result, however, rests on the model specification tests. In dynamic panel models, instruments of the lagged dependent variable would be valid only if the presence of the remaining serial correlation in the idiosyncratic error term is ruled out. The Arellano–Bond serial correlation test reveals the absence of second-order serial correlation in system GMM errors. The Hansen test of the overidentifying restrictions test confirms the joint validity of overidentification restrictions for two-stage-system GMM estimators. The Difference-in-Hansen test for the validity of the additional moment conditions for the level model in the two-stage system GMM presented in column (5) also affirms that supplementary overidentifying restrictions are valid with a p-value of 0.116.

The additional moment conditions for the level model in the system GMM estimator can help overcome weak instrument problems even when the series is very persistent (Bun & Windmeijer 2010) and leads to better finite sample properties in terms of bias (Blundell & Bond 1998, Blundell et al. 2001). The proliferation instruments, however, may introduce an underidentification problem. To reduce the weak instrument problem induced by the proliferation of instruments, we collapse and curtail the instruments. The instruments used in this paper are weakly related to the endogenous variables. As Roodman (2009) and Windmeijer (2005) indicate, however, the two-stage system GMM provides asymptotically efficient, robust, and reliable results when facing endogeneity and heteroscedasticity.

The result based on a two-stage system GMM estimator, our preferred estimation method, is presented in column (5) of Table 2.3. The result shows that in comparison to the static model, FDI turns out to be significant at a 10% significance level. A 1% increase in the share of the firm's foreign capital in the short run increased the share of skilled labor wage by 0.013 or 1.3 percentage points. In the long run, a 1% increase in FDI increases the share of skilled labor wages by about 1.7 percentage points.[14] The total change in the

[13]The estimate for the coefficient on lagged dependent variable also lies between the bounds of OLS estimate of 0.457 and fixed effect estimates of -0.208. Adding regional-year and sector-year fixed effects and interaction provides a coefficient estimate of 0.412 and -0.209 respectively for OLS and FE, and confirms that the system GMM is the right estimation method(see, Table B.9).

[14]The long-run effect is calculated as $(\beta_4/1-\alpha_1)$ based on equation(3).

share of skilled labor wages from 2013 to 2017 was 0.015, while the log change in FDI was -0.184. Multiplying the estimated effect of FDI in the long run, 0.017, with the growth of FDI over the period implies that the share of skilled labor wage would have increased by around 16% had FDI remained at the 2013 level.[15] To check for the robustness of the result for different samples, we estimate the model for the sample of firms that include firms with less than 10 labor employment. The result presented in Column(6) indicates that the result is robust to the change in the sample size. Nonetheless, we cannot ascribe the rise in the share of skilled labor wage to skilled-biased technological change since the industry didn't undergo a shift in skilled labor demand over the study period despite the increase in relative wage.

Looking at the parameter estimates, the coefficient estimate in the two-stage system-GMM estimate is higher than what we found in the FDGLS estimation method for the static model. It suggests that failure to consider the persistence of skilled labor wage share could underestimate the effect of FDI on the share of skilled labor wage. Yet, the estimated effect of FDI is still very small relative to what Lee & Wie (2015) found for Indonesia and Feenstra & Hanson (1997) for Mexico. The small effect of FDI on the share of skilled labor wages may suggest that though foreign firms pay relatively better wages, they have little incentive to pay higher wages due to the prevalence of high unemployment in the country. The possible justification for this could be related to different factors. First, the 2012 Ethiopia's industrial policy sought to attract FDI to footloose industries; and the country joined the global apparel production network recently (Oya & Schaefer 2021). As a result, the skilled workers in foreign firms may lack the experience that could be translated to higher productivity, thereby limiting the growth of their wage bill share. The recent report on the skill of non-production workers in Ethiopian light manufacturing industry by Oya et al. (2022) confirms that most managers did not have the relevant experience when hired and had to go through different training schemes starting from rather low levels to understand the required skills in the industry.

Second, it could also be related to the prevalence of high unemployment of both skilled

[15] ln(FDI) decreased from 0.363 in 2013 to 0.180 in 2017. The contribution of FDI to the share of skilled labor wage is calculated as $\frac{(0.018)\times(-0.184)}{(0.015)}$.

and unskilled labor that foreign-invested firms want to take advantage of. Compared to East Asian countries that have experienced a rise in wages in recent years, the high unemployment in Ethiopia provides foreign firms a lower cost advantage to compete in the international market (Gelb et al. 2017). In such labor market settings, foreign firms would be reluctant to pay higher wages for skilled workers as the cost of losing skilled labor is low.

The result for other variables in the specification is interesting as well. Compared to the static model, significant variables continue to be significant, and the estimated coefficient of output improves in magnitude. The estimated effect of capital is still insignificant and suggests the lack of convincing evidence for capital and skilled labor complementarity in Ethiopia during the study period. The other measure of technology adoption, export, is also significant and improves in magnitude though still negative suggesting that exporting firms in developing countries specialize in labor-intensive products that depend mainly on production workers.

### 2.6.3 Robustness of the results

In this section, we provide a robustness analysis in addition to the sensitivity of the result to the changes in the sample of firms presented in column(6) of Table 2.3. It is common in the literature that FDI is also defined as an indicator variable of whether a firm is a foreign firm or not. A firm is defined as a foreign if it has a foreign share in its total paid capital. The test for the selection of estimation strategy and specification tests for the static model indicates the absence of endogeneity but the presence of serial correlation in the original error term. The static model is thus estimated using FDGLD. To control for the possible persistence of skilled labor wage bill share, we estimate the dynamic model. Like the case where FDI is measured as foreign capital share, we treat capital, output, relative wage, and Foreign as endogenous variables in addition to the lagged dependent variable.

In the estimation of the dynamic model, we allowed these variables and the lagged dependent variables to be endogenous while the other explanatory variables were treated

Table 2.4: Robustness of the result: FDI is defined as indicator variable

| | Only for labor >=10 | | | Include labor <10 | |
|---|---|---|---|---|---|
| | (1) FDGLS | (2) sGMM1 | (3) sGMM2 | (4) sGMM1 | (5) sGMM2 |
| L.Share | - | 0.203*** | 0.208*** | 0.218*** | 0.208*** |
| | | (0.051) | (0.053) | (0.048) | (0.053) |
| ln(Capital) | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| ln(Output) | -0.010** | -0.017** | -0.016** | -0.017*** | -0.016** |
| | (0.005) | (0.007) | (0.007) | (0.006) | (0.007) |
| ln(Relative wage) | 0.076*** | 0.076*** | 0.077*** | 0.068*** | 0.077*** |
| | (0.008) | (0.012) | (0.012) | (0.012) | (0.012) |
| Foreign | 0.028* | 0.059** | 0.057* | 0.059** | 0.057* |
| | (0.015) | (0.029) | (0.030) | (0.030) | (0.030) |
| ln(Export) | -0.101** | -0.128* | -0.151** | -0.157** | -0.151** |
| | (0.046) | (0.071) | (0.073) | (0.075) | (0.073) |
| ln(Import) | -0.001 | -0.001 | -0.010 | 0.004 | -0.010 |
| | (0.015) | (0.026) | (0.026) | (0.025) | (0.026) |
| Observations | 3288 | 3288 | 3288 | 3578 | 3288 |
| AB(1) | - | 0.000 | 0.000 | 0.000 | 0.000 |
| AB(2) | - | 0.592 | 0.610 | 0.868 | 0.610 |
| Hansen-J(P-value) | - | - | 0.328 | - | 0.328 |
| Difference-in-Hansen | - | - | 0.157 | - | 0.328 |

N.B.: The Table shows the result when FDI is defined as an indicator variable, Foreign. FDGLS refers to the first difference generalized least square estimator while "sGMM1" and "sGMM2" respectively refer to the one-stage and two-stage system-GMM estimator. The exogenous variables are output, foreign, imports, and exports. Robust standard errors clustered at the firm level are in parentheses. The specification test statistics are the Arellano and Bond, AB, test for serial correlation, the Hansen over-identification test, and the Difference-in Hansen test for the exogeneity of the additional instruments of the level equation. *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

as strictly exogenous. As a result, the instrumental variables remain the same as in the case where the FDI is defined as foreign capital share. The dynamic model specification tests for the two-stage system GMM confirm the model is well specified as the tests indicate the absence of second-order serial correlation, the validity of the overidentification restriction, and the addition moment conditions for the level model. Table 2.4 presents the result when FDI is defined as an indicator variable.

The result based on the static model estimated using the FDGLS method in column

(1) indicates that the Foreign indicator, Foreign, is found to have a positive effect on the wage share of skilled labor at a 10% significant level and relatively with a higher magnitude. Firms with foreign capital, on average, have more skilled labor wage bill share than domestic firms. Output and relative wage continue to be significant while capital is still insignificant. The coefficient on a firm's export share is estimated to be still negative and significant at a 5% significant level suggesting an increase in a firm's export share decreases the share of the skilled labor wage bill, which is not unexpected in developing countries as explained before. The result from the two-stage system-GMM, our preferred estimation method, presented in column (3) for the dynamic model indicates that the indicator variable for FDI, Foreign, increases in magnitude and becomes significant at the same 10% significance level. The share of skilled labor wages in foreign firms, on average, is higher than domestic firms by about 0.057 or 5.7 percentage points suggesting that FID increases the share of skilled labor wages. Column (5) presents the result when the dynamic model is estimated for another sample of firms with less than 10 number of labor employment. The conclusion still holds that FDI increases the share of skilled labor wage in foreign firms. The result is consistent with the result presented in Figure 2.4 which indicates that foreign firms pay relatively higher wages than their domestic counterparts, and confirms that the positive impact of FDI on skilled labor wage share is robust to different variable definitions of FDI.

### 2.6.4 What explains the rise in wage inequality?

There exists an agreement in the inequality literature that wage inequality between skilled and unskilled workers in many developing countries is driven by an increase in the demand for skilled workers (Goldberg & Pavcnik 2007). The positive correlation between the share of the skilled labor wage bill and FDI in the literature is interpreted as an increase in skilled labor demand or skill upgrading attributed to SBTC induced by technology adaption (Lee & Wie 2015, Pavcnik 2003). Feenstra & Hanson (1997) relate the wage inequality in Mexico to the skewed labor demand toward skilled labor by foreign firms. The effect of FDI on the rise in the share of skilled labor wage that we found earlier for the Ethiopian manufacturing industry, however, occurred during the period when the industry experienced a decline in the proportion of skilled labor. This confirms that the manufacturing industry didn't undergo a SBTC during the period from 2013 to 2017. As discussed earlier, this could be attributed to the importance of the manufacturing industry to unskilled labor. Moreover, Harrison & Hanson (1999) argues that, with skilled workers' wage bill share as the dependent variable, it is difficult to attribute the rise in the share of skilled labor wage to either an increase in wages, an increase in skilled labor employment, or both.

It is therefore difficult to ascribe the rise in the share of skilled labor wage to the increase in wages or an increase in skilled labor demand of foreign-invested firms. If so, what is the source of the rise in the share of skilled labor wage? Is it an increase in wages that responded to technology adoption through FDI? Or an increase in skilled labor employment level, or both? To answer these questions, we estimate equation (3) where the dependent variable is skilled labor proportion. The test for the strict exogeneity of the regressors in the first difference of equation (2) of the static model using the feedback effect approach as outlined in Wooldridge (2010, Chapter 10.7.1) indicates that capital, relative wage, and the foreign dummy violate the strict exogeneity assumption. Since the literature indicates output as an endogenous variable, we also treated output as endogenous variables in the dynamic model in addition to capital, relative wage, foreign dummy, and the lagged dependant variable, and estimated the dynamic model of equation(3) using system-GMM estimator[16]. We use the same internal instruments discussed in section 2.6.2.

Table 2.5 presents the results of the model with skilled labor proportion as the dependent variable. The model specification tests confirm that there is no second-order serial correlation and that the overidentification restrictions are valid. The second-stage system-GMM estimates in column (2) show that FDI, measured as a firm's share of foreign capital, has a positive and significant effect on skilled labor demand (skill upgrading) at a 10% significant level. Though the magnitude of the coefficient estimates is small, the results suggest that firm-level technology adoption through FDI led to an increase

[16]The test of exogeneity results for the static model using the feedback effect is presented in Table B.7.

Table 2.5: Skilled labor proportion regression

| | FDI as foreign capital share | | FDI as dummy | |
|---|---|---|---|---|
| | (1) sGMM1 | (2) sGMM2 | (3) sGMM1 | (4) sGMM2 |
| L.SKLShare | 0.275*** | 0.269** | 0.290*** | 0.270** |
| | (0.104) | (0.116) | (0.097) | (0.116) |
| ln(Capital) | 0.002 | 0.002 | 0.003 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(Output) | -0.012** | -0.011** | -0.015*** | -0.011** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| ln(Relative wage) | -0.096*** | -0.096*** | -0.100*** | -0.096*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| ln(FDI) or Foreign | 0.010* | 0.010* | 0.037* | 0.039* |
| | (0.006) | (0.006) | (0.022) | (0.022) |
| ln(Export) | -0.114* | -0.107* | -0.118* | -0.108* |
| | (0.063) | (0.063) | (0.063) | (0.063) |
| ln(Import) | 0.009 | 0.011 | 0.014 | 0.012 |
| | (0.019) | (0.019) | (0.018) | (0.019) |
| Observations | 3288 | 3288 | 3578 | 3288 |
| AB(1) | 0.000 | 0.000 | 0.000 | 0.000 |
| AB(2) | 0.897 | 0.894 | 0.933 | 0.904 |
| Hansen-J($Chi^2$) | - | 7.385 | - | 7.451 |
| Hansen-J(P-value) | - | 0.831 | - | 0.826 |
| Difference-in-Hansen | - | 0.584 | - | 0.579 |

N.B.: In Columns (1) and (2) FDI is defined as a share of foreign capital while in columns (4) and (5) is defined as an indicator variable, Foreign."sGMM1" and "sGMM2" refer to the one-stage and two-stage system-GMM estimator respectively. The exogenous variables are, in all cases, output, imports, and exports. Standard errors robust to serial correlation and heteroskedasticity are in parentheses. The specification test statistics are the Arellano and Bond(AB), test serial correlation, and the Difference-in Hansen test for the exogeneity of the additional instruments of the level equation. *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

in firm-level employment of skilled labor in the Ethiopian manufacturing industry in the period from 2013 to 2017.[17]

This finding is robust to different definitions of FDI as an indicator variable in column(5) and suggests the presence of SBTC at the firm level through technology adoption

[17] We also estimate the model where only the lag-dependent variables and the three endogenous variables identified using the feedback effect, capital, relative wage, and foreign in the static model, are treated as endogenous variables. Table B.10 indicates that the result is the same.

using FDI. Our analysis confirms that within-firm SBTC is underway in the Ethiopian manufacturing industry and that a within-firm shift in skilled labor demand is driving the rise in wage inequality in the later years of the study period. The result suggests that even in labor markets where skilled and unskilled labor is abundant, foreign firms can pay higher wages to attract and retain skilled labor, leading to within-firm skill upgrading and technological change. The lack of industry-level SBTC in Ethiopia could therefore be due to the nature of FDI flowing into the country. Recent FDI inflows into the Ethiopian manufacturing industry have been concentrated in labor-intensive sectors such as textiles, garments, and leather and leather products, which are identified as priority sectors for industrial development by the government of Ethiopia. These sectors rely heavily on production workers and may not necessarily lead to an increase in the employment of skilled labor at the manufacturing industry level. The small number of foreign firms in the manufacturing industry (only 8.2%) may also explain the lack of industry-level SBTC.

## 2.7 Conclusion

This study examined wage inequality in Ethiopian manufacturing firms from 2013 to 2017 and whether FDI explains this inequality. Since 2002, Ethiopia has implemented an export-oriented industrial policy that emphasizes FDI as a source of skill development and growth. This policy, which was strengthened in 2012, led to a rapid increase in FDI in the manufacturing industry. Our analysis of survey data shows that while the share of skilled workers fell, wage disparity between skilled and unskilled labor began to increase in 2015. However, the findings suggest that the Ethiopian manufacturing sector has not yet experienced SBTC, and the industry remains less skilled and labor-intensive.

We used a formal approach to further investigate the role of FDI and international trade in explaining rising wage inequality. The regression analysis showed that FDI increased the wage bill shares of non-production workers, but the estimated effect was very small compared to other developing countries. The skilled labor proportion regression also showed that FDI had a positive and significant effect on the share of skilled labor employment, suggesting skill upgrading within firms. Therefore, firm-level skilled labor employment is the driving force behind the rise in wage inequality observed in the later years of the study period.

These findings have important policy implications for developing countries that have recently joind the global value chain and want to achieve industrial development. First, due to their lower labor costs, these countries may attract FDI flows driven by the international competitiveness of their local production. Foreign-invested firms in these cases can increase their productivity by paying relatively high wages to the few skilled workers they employ because these workers have better exit options and greater bargaining power. This can lead to higher wage inequality in the manufacturing sector. The findings suggest that the relationship between FDI, wage inequality, and skill upgrading will continue to be a key policy and research concern for developing countries that have recently begun to participate in the global value chain. This is particularly important given the high levels of unemployment in these countries, as FDI presents a policy dilemma: creating employment opportunities for the unemployed while also reducing inequality.

Second, the nature of FDI, the small number of foreign firms, and the characteristics of the labor force could have played a major role in the Ethiopian manufacturing industry's failure to achieve SBTC. The absence of industry-level SBTC presents an important policy challenge for policymakers who aspire to achieve technological change and industrial development. As a result, policies designed to encourage FDI in developing countries should focus not only on light manufacturing but also on sectors with the potential to drive industry-level technological change and serve as the basis for future industrial development. These policies should also be complemented with labor and social policies to increase the skills and competency levels of unskilled workers and abate the possibility of wage inequality. One caveat of this paper is the use of only five years of data to answer the question of SBTC, which is mainly a long-run phenomenon. Investigating the question using longer period data would provide a better understanding of the SBTC in the Ethiopian manufacturing sector in the future.

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# Appendix B

# Figures and Tables

Figure B.1: Proportion of skilled labor for the balanced panel

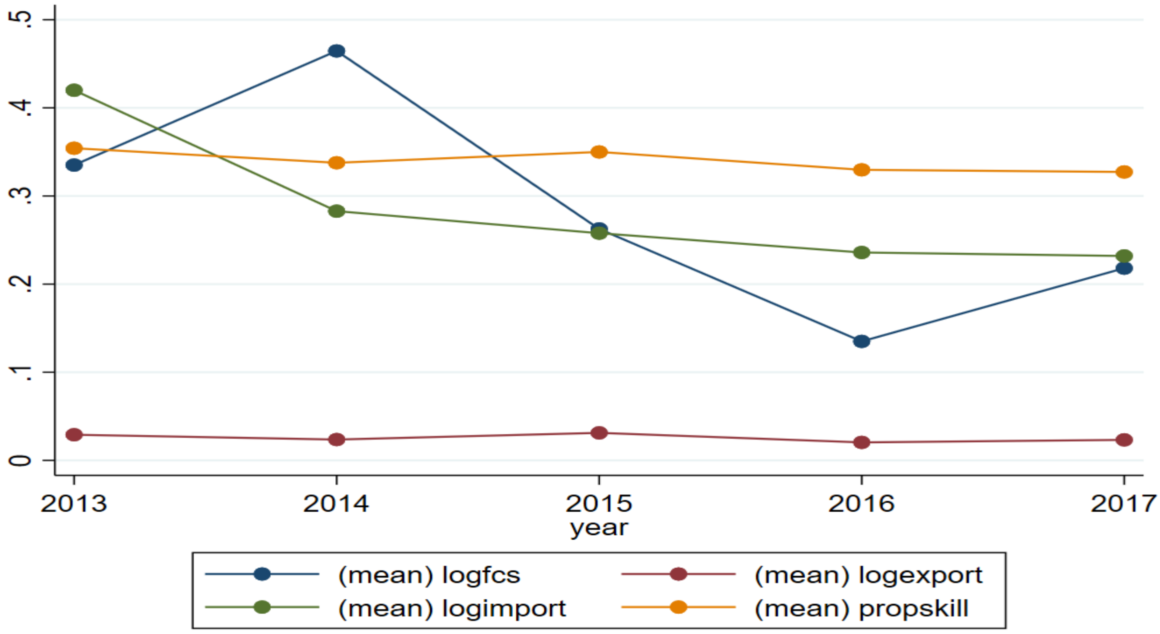


Table B.1: Classification of sectors into two technology groups

| Unskilled labor intensive | Skilled labor intensive |
|---|---|
| Food and beverages | Chemicals |
| Textiles | Rubber and plastics |
| Garment | Non-metallic mineral |
| Leather | Basic metals |
| Wood | Fabricated metal products |
| Paper | Machinery and equipment |
| Publishing | Computing, electrical and furniture |

*N.B.:* CSS does not have a sectoral classification that groups manufacturing industries(sectors) into high-tech or low-tech industries. To classify the sectors into skilled and unskilled labor-intensive groups, we used the European Statistical Classification (ESC) of economic activities, NACE Rev.2, which is comparable to the Ethiopian manufacturing sector two-digit classification of firms that are skilled and unskilled labor-intensive. Thus industries that are classified as medium-tech industries in the ESC are grouped as capital-intensive industries in our classification and low-tech industries as grouped as labor-intensive.

Table B.2: Number of foreign and domestic firms by region over the years

| | Year | | | | | |
|---|---|---|---|---|---|---|
| Region | Firm ownership | 2013 | 2014 | 2015 | 2016 | 2017 |
| Tigray | Foreign | 79 | 88 | 102 | 130 | 110 |
| | Domestic | 0 | 0 | 2 | 0 | 1 |
| Afar | Foreign | 1 | 3 | 5 | 6 | 5 |
| | Domestic | 0 | 0 | 0 | 0 | 0 |
| Amhara | Foreign | 109 | 77 | 135 | 195 | 179 |
| | Domestic | 4 | 6 | 5 | 4 | 8 |
| Oromia | Foreign | 373 | 324 | 448 | 518 | 385 |
| | Domestic | 53 | 47 | 69 | 32 | 24 |
| Somali | Foreign | 14 | 10 | 13 | 19 | 15 |
| | Domestic | 0 | 0 | 0 | 0 | 0 |
| Benishangul | Foreign | 2 | 2 | 4 | 4 | 3 |
| | Domestic | 0 | 0 | 0 | 0 | 0 |
| S.N.N.P | Foreign | 147 | 124 | 190 | 222 | 179 |
| | Domestic | 0 | 2 | 2 | 0 | 0 |
| Harari | Foreign | 16 | 18 | 15 | 17 | 25 |
| | Domestic | 0 | 0 | 0 | 1 | 1 |
| AddisAbaba | Foreign | 323 | 296 | 362 | 549 | 384 |
| | Domestic | 44 | 37 | 32 | 25 | 24 |
| DireDawa | Foreign | 35 | 32 | 60 | 67 | 62 |
| | Domestic | 0 | 3 | 1 | 1 | 4 |
| | Total Foreign Firms | 74 | 96 | 88 | 57 | 90 |
| | Total Domestic Firms | 1,074 | 1,217 | 1,342 | 1,778 | 1,948 |
| | Total Firms | 1,148 | 1,313 | 1,430 | 1,835 | 2,038 |

*N.B.:* A firm is defined as a foreign firm if it has a foreign capital share in its total paid-up capital

Table B.3: Technology use over years

| | FDI | Export | Import |
|---|---|---|---|
| 2013 | 0.36 | 0.03 | 0.41 |
| 2014 | 0.38 | 0.03 | 0.27 |
| 2015 | 0.33 | 0.02 | 0.24 |
| 2016 | 0.15 | 0.01 | 0.23 |
| 2017 | 0.18 | 0.01 | 0.22 |

N.B.: The technology measures are expressed in a natural logarithm.

Table B.4: Sectoral distribution of foreign firms and wage by ownership type

| | | | Mean log wage for skilled labor | |
|---|---|---|---|---|
| S.No. | Sectors | Number of foreign firms | Domestic | Foreign |
| 1 | Food and beverages | 91 | 6.985 | 7.505 |
| 2 | Textiles | 34 | 7.137 | 6.980 |
| 3 | Garment | 12 | 6.690 | 7.007 |
| 4 | Leather | 35 | 6.825 | 7.057 |
| 5 | Wood | 8 | 6.858 | 7.305 |
| 6 | Paper products | 17 | 7.297 | 7.293 |
| 7 | Printing | 6 | 7.127 | 7.742 |
| 8 | Chemicals | 64 | 7.221 | 7.289 |
| 9 | Rubber and plastics | 38 | 7.067 | 7.326 |
| 10 | Non-metallic mineral | 40 | 6.874 | 7.123 |
| 11 | Basic metals | 17 | 7.512 | 7.784 |
| 12 | Fabricated metals | 36 | 7.144 | 7.739 |
| 13 | Machinery and equipment | 16 | 7.305 | 7.350 |
| 14 | Vehicles and transport | 3 | 7.861 | 8.310 |
| 15 | Furniture | 15 | 6.791 | 7.090 |

N.B.: A firm is defined as a foreign firm if it has a foreign capital share in its total paid-up capital.

Table B.5: Manufacturing export by sector over the years

| | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|
| Food and beverage | 93.60 | 102.40 | 131.60 | 138.80 | 143.40 |
| Textile and garment | 97.40 | 110.20 | 97.80 | 77.80 | 89.30 |
| Leather and leather products | 121.07 | 129.81 | 131.58 | 115.28 | 114.00 |
| Chemicals and pharmaceuticals | - | 3.10 | 17.80 | 15.90 | 17.20 |
| Metals | - | 0.20 | 10.50 | 0.80 | 0.80 |
| Electronics | - | - | - | - | - |
| Total | 312.00 | 345.80 | 389.4 | 348.7 | 364.80 |
| Labor intensive export share | 100.00 | 99.02 | 92.7 | 295.2 | 295.05 |

*N.B.:*: Manufacturing export by sector over the years is obtained from the National Bank of Ethiopia

Table B.6: Test for selection bias

| | (1) FDI as log of share of foreign capital | (2) FDI as indicator variable Foreign |
|---|---|---|
| ln(Capital) | 0.002 | 0.002 |
| | (0.002) | (0.002) |
| ln(Output) | -0.016*** | -0.016*** |
| | (0.005) | (0.005) |
| ln(Relative wage) | 0.059*** | 0.059*** |
| | (0.008) | (0.008) |
| ln(FDI) or Foreign | 0.007* | 0.037** |
| | (0.004) | (0.017) |
| ln(Export) | -0.096* | -0.095* |
| | (0.056) | (0.056) |
| ln(Import) | -0.005 | -0.005 |
| | (0.015) | (0.015) |
| lagmiss | 0.013 | 0.013 |
| | (0.009) | (0.009) |
| Observations | 5713 | 5713 |
| Adjusted $R^2$ | 0.079 | 0.079 |

N.B.: The regression includes time, sector, and regional dummies. Standard errors robust to serial correlation and heteroskedasticity are in parentheses.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table B.7: Test for Endogeneity using feedback effect when the dependant variable Share of skilled labor wage

| | Skilled labor wage share | | Skilled labor proportion | |
|---|---|---|---|---|
| | (1) Foreign capital share | (2) Foreign dummy | (3) Foreign capital share | (4) Foreign dummy |
| D.ln(Capital) | 0.001 | 0.002 | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| D.ln(Output) | -0.010** | -0.011** | -0.011*** | -0.011*** |
| | (0.005) | (0.005) | (0.004) | (0.004) |
| D.ln(Relative wage) | 0.076*** | 0.074*** | -0.075*** | -0.075*** |
| | (0.009) | (0.009) | (0.006) | (0.006) |
| D.ln(FDI) or D.Foreign | 0.008* | 0.045*** | 0.006* | 0.030** |
| | (0.004) | (0.018) | (0.003) | (0.014) |
| D.ln(Export) | -0.107** | -0.099* | -0.022 | -0.022 |
| | (0.051) | (0.052) | (0.038) | (0.038) |
| D.ln(Import) | -0.013 | -0.015 | 0.020 | 0.020 |
| | (0.018) | (0.018) | (0.014) | (0.014) |
| ln(Capital) | 0.001 | 0.000 | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(Output) | 0.002 | 0.003 | 0.007*** | 0.007*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| ln(Relative wage) | -0.002 | -0.001 | 0.010* | 0.010* |
| | (0.008) | (0.008) | (0.005) | (0.005) |
| ln(FDI) or Foreign | -0.003 | -0.018 | -0.004* | -0.020* |
| | (0.003) | (0.013) | (0.002) | (0.010) |
| ln(Export) | 0.018 | 0.014 | -0.009 | -0.009 |
| | (0.028) | (0.029) | (0.023) | (0.023) |
| ln(Import) | 0.013 | 0.015 | -0.015 | -0.014 |
| | (0.015) | (0.015) | (0.012) | (0.012) |
| Observations | 3288 | 3288 | 3288 | 3288 |
| Adjusted $R^2$ | 0.075 | 0.087 | 0.141 | 0.142 |

N.B.: The table presents the test for the strict exogeneity of the regressors in the first difference equation as outlined in (Wooldridge 2010, Chapter 10.7.1) when the dependant variable is share of skilled labor wage. The regression includes time, sector, and regional dummies and year-region and year-sector fixed effects. Capital and relative wage are statistically significant and indicate that these variables fail the strict exogeneity assumption. Standard errors robust to serial correlation and heteroskedasticity are in parentheses.*p < 0.10, **p < 0.05, ***p < 0.01.

Table B.8: Model selection criteria from two-stage system GMM estimator

| | (1) No lag of explanatory variable | (2) With lag of explanatory variable |
|---|---|---|
| L.Share | 0.204*** | 0.128 |
| | (0.054) | (0.116) |
| ln(Capital) | 0.002 | 0.006 |
| | (0.003) | (0.033) |
| ln(Output) | -0.015** | 0.019 |
| | (0.007) | (0.044) |
| ln(Relative wage) | 0.076*** | 0.092** |
| | (0.012) | (0.041) |
| ln(FDI) | 0.017** | 0.013 |
| | (0.007) | (0.015) |
| ln(Export) | -0.161** | -0.049 |
| | (0.068) | (0.361) |
| ln(Import) | -0.014 | -0.127 |
| | (0.026) | (0.093) |
| L.ln(Capital) | - | 0.009 |
| | | (0.051) |
| L.ln(Relative wage) | - | 0.002 |
| | | (0.049) |
| L.ln(Output) | - | 0.048 |
| | | (0.055) |
| L.ln(FDI) | - | 0.004 |
| | | (0.012) |
| L.ln(Export) | - | 0.010 |
| | | (0.395) |
| L.ln(Import) | - | -0.128 |
| | | (0.107) |
| Observations | 3288 | 3288 |
| Hansen-J(P-value) | 0.427 | 0.451 |
| MMSC-AIC | -13.6969 | -4.3219 |
| MMSC-BIC | -91.5963 | -26.5789 |
| MMSC-HQIC | -42.9196 | -12.6712 |

N.B.: The table presents the result of Andrews and Lu (2001) model and moment selection criteria from sGMM2 methods. Column (1) includes the lag of the dependent variable while column (2) includes the first lag of the dependent variable and explanatory variables. Standard errors robust to serial correlation and heteroskedasticity are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table B.9: OLS and FE estimates of dynamic model

| | No Fixed Effect | | With Fixed Effect | |
|---|---|---|---|---|
| | (1) OLS | (2) FE | (3) OLS | (4) FE |
| L.Share | 0.457*** | -0.208*** | 0.422*** | -0.219*** |
| | (0.016) | (0.033) | (0.017) | (0.034) |
| ln(Capital) | 0.006*** | 0.003 | 0.006*** | 0.003 |
| | (0.001) | (0.002) | (0.002) | (0.003) |
| ln(Output) | 0.005** | -0.009 | 0.002 | -0.010* |
| | (0.002) | (0.006) | (0.002) | (0.006) |
| ln(Relative wage) | 0.047*** | 0.107*** | 0.048*** | 0.103*** |
| | (0.005) | (0.013) | (0.005) | (0.013) |
| ln(FDI) | -0.001 | 0.003 | -0.002 | 0.001 |
| | (0.004) | (0.005) | (0.004) | (0.005) |
| ln(Export) | -0.081** | 0.039 | -0.050 | 0.006 |
| | (0.033) | (0.063) | (0.035) | (0.063) |
| ln(Import) | 0.001 | -0.006 | 0.025* | -0.008 |
| | (0.013) | (0.020) | (0.015) | (0.020) |
| Observations | 3288 | 3288 | 3288 | 3288 |
| Adjusted $R^2$ | 0.231 | 0.194 | 0.261 | 0.245 |

N.B.: The Table shows the OLS and Fixed effect results of the dynamic model. *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

Table B.10: Skilled labor proportion regression

| | FDI as foreign capital share | | FDI as dummy | |
|---|---|---|---|---|
| | (1) sGMM1 | (2) sGMM2 | (3) sGMM1 | (4) sGMM2 |
| L.Skill labor proportion | 0.288*** | 0.291** | 0.299*** | 0.292** |
| | (0.107) | (0.117) | (0.100) | (0.117) |
| ln(Capital) | 0.002 | 0.002 | 0.003 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(Output) | -0.012** | -0.011** | -0.015*** | -0.011** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| ln(Relative wage) | -0.097*** | -0.097*** | -0.101*** | -0.097*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| ln(FDI) or Foreign | 0.010* | 0.010* | 0.037* | 0.039* |
| | (0.006) | (0.006) | (0.022) | (0.022) |
| ln(Export) | -0.114* | -0.107* | -0.118* | -0.108* |
| | (0.063) | (0.063) | (0.063) | (0.063) |
| ln(Import) | 0.009 | 0.012 | 0.014 | 0.012 |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Observations | 3288 | 3288 | 3578 | 3288 |
| AB(1) | 0.000 | 0.000 | 0.000 | 0.000 |
| AB(2) | 0.905 | 0.906 | 0.925 | 0.916 |
| Hansen-J($Chi^2$) | - | 6.757 | - | 6.800 |
| Hansen-J(P-value) | - | 0.818 | - | 0.815 |
| Difference-in-Hansen | - | 0.619 | - | 0.613 |

N.B.: In Columns (1) and (2) FDI is defined as a share of foreign capital while in columns (4) and (5) it is defined as an indicator variable, Foreign."sGMM1" and "sGMM2" refer to the one-stage and two-stage system-GMM estimator respectively. The endogenous variables in all cases are the lag-dependent variable, capital, relative wage, and FDI (Foreign). Standard errors robust to serial correlation and heteroskedasticity are in parentheses. The specification test statistics are the Arellano and Bond, AB, test serial correlation and the Difference-in-Hansen test for the exogeneity of the additional instruments of the level equation. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

# Chapter 3

# Liquidity shock and bank lending: Evidence from a natural experiment in Ethiopia.

**Abstract:**

The financial system in many developing countries is dominated by banking systems with underdeveloped inter-bank markets, which limits the effectiveness of the bank lending channel. This paper exploits the mandatory regulatory requirement on new bill purchases as a natural experiment and provides evidence of the causal impact of the bank lending channel of liquidity shocks in the developing country, Ethiopia. The result from an event study design shows that banks whose liquidity was affected by the regulation reduced lending, confirming the prevalence of bank lending channels in developing countries. Specifically, for the same firm-cluster borrowing from two groups of banks exposed to a differential liquidity shock, the average loan and loan repayment period from treated banks decreased over the study period. These effects also persisted in a relatively longer event window. The result thus indicates that the regulation caused banks to engage in credit rationing by providing small-sized loans with higher repayment frequency to a large number of borrowers, thereby increasing the volume of loan supply by better-capitalized banks.

*Keywords: Regulation, liquidity shock, loan supply, Ethiopia*

*JEL Classification:E510 G28*

## 3.1 Introduction

Banks in developing countries are a major source of finance for small and medium-sized businesses (Weisbrod & Rojas-Suárez 1995, Mishra et al. 2014). Liquidity shock to the banking industry can have a detrimental impact on firms' investment and short-term growth. The effect could be exacerbated if banks' access to short-term external liquidity is limited due to the isolation of the banking sector from the international market since firms cannot issue short-term liability to raise capital. Empirical evidence from developed (Kashyap & Stein 2000, Jiménez et al. 2012) and emerging economies (Khwaja & Mian 2008) shows that banks pass liquidity shocks on to borrowers even when there is no change in their overall creditworthiness. Recent studies in developing countries in Uganda (Abuka et al. 2019) and Peru (Schnabl 2012) also show the transmission of a liquidity shock to the real economy. Many developing countries, however, are still characterized by underdeveloped inter-bank markets (Fischer 2015), weak legal environments and concentrated banking systems (Mishra et al. 2014), and excess liquidity (Saxegaard 2006) restricting the functioning of the credit channel.

However, the extent to which banks in developing countries transmit liquidity shocks to borrowers and the transmission mechanisms remain unclear. This paper examines the causal impact of liquidity shocks in a developing country where standard monetary policy targeting interest rates is absent. Examining the causal impact of liquidity shocks on bank lending behavior poses significant identification challenges for two reasons. First, liquidity shocks are typically systemic and affect all banks simultaneously, making it difficult to identify how a universal liquidity shock exposes banks to differential liquidity shocks. Second, loan supply is endogenous to banks' lending policies and is also affected by macroeconomic shocks through both the bank lending and firm borrowing channels. Firms affected more by monetary conditions may borrow more from affected banks (Gertler & Gilchrist 1994). Similarly, banks experiencing a liquidity shock might face a simultaneous decline in firms' credit demand. Quantifying the bank lending channel of liquidity shock requires separating the credit supply from credit demand.

To obtain exogenous variation in banks' exposure to liquidity shocks, this study uses the mandatory regulatory policy change on new bill purchases implemented by the National Bank of Ethiopia (NBE) in April 2011 as a natural experiment. The sudden announcement and immediate application of the regulation exposed banks to differential liquidity shocks. This study exploits the exogenous cross-sectional difference in pre-regulation bank capital for the identification strategy. Banks are then assigned to two cohorts based on their exposure to the liquidity shock. The hypothesis is that relative to under-capitalized (small) banks, better-capitalized banks (larger) banks, which used to lend more before the regulation, will continue lending more even after the regulation because of their greater availability of loanable funds. Since the regulation is attached to each new loan disbursement, banks that are lending more after the regulation will experience liquidity drainage as they buy more NBE bill. This will eventually lead to less lending by the group of banks which was lending more.

Critical to the identification strategy is the use of two confidential data sources from NBE: supervisory bank balance sheet data and credit register loan-level microdata. The first data are used to examine the impact of the policy change on bank liquidity and understand the transmission mechanism. The second data source covers all types of loans extended by all commercial banks and helps to overcome the empirical identification challenge of separating credit demand and supply. However, due to the prevalence of a significant number of single-bank borrower relationships, the data are constructed at the firm cluster: the cluster being industry and region.

The result from the event study design shows that banks in Ethiopia transmit liquidity shocks both in the intensive and extensive margin of lending, confirming the presence of a bank lending channel of liquidity shocks. Specifically, in the intensive margin,[1] large banks whose cash on hand declined by an average of 128.2% in the 10 months reduced the average loan size over the same period while increasing the total volume of loans, relative to pre-regulation month. The result is the same in the long event window where the post-treatment period is extended to 13 months. The result is similar to the finding of Abuka et al. (2019) for Uganda where a change in short-term interest reduces the bank

[1] Intensive margin refers to the amount lent by banks and is measured as total loan and average loan while the extensive margin is the number of outstanding loans and the number of times a loan is repaid.

credit supply from banks with more leverage. In the extensive margin, the results also show that large banks increased loan repayment frequency and the number of outstanding loans both in the short and long event windows. The findings show that the policy change caused banks to engage in credit rationing by providing small-sized denominated loans with high repayment frequency to a large number of borrowers thereby increasing the total volume in both event windows. The finding is consistent with the idea that balance sheet strength plays a major role in monetary policy transmission and the impact of monetary policy on lending behavior is small for better-capitalized banks (Bernanke & Gertler 1995, Kashyap & Stein 2000).

A natural challenge in this setting is the identification strategy that groups banks based on their exposure to the regulation (treatment intensity). Ex-ante differences in bank characteristics between the two groups of banks could have led to different liquidity and bank loan supply trends even in the absence of the policy change. To overcome these problems, the study undertook several pre-trend tests and additional sensitivity analyses as recommended by Rambachan & Roth (2023). Thus, the results are robust to violations of the parallel trend assumption, which imposes smoothness linear restrictions. The event windows are also selected so that the possible confounding factors that can affect banks' liquidity and lending behavior are eliminated. The study thus restricts the analysis to the first 10 to 13 months after the policy change, during which no other policy changes were expected to impact banks' loan supply.

The paper contributes to various strands of literature on bank lending channel and liquidity shock. First, the study contributes to the empirical literature which shows the effect of monetary policy shock on the supply of credit depends on the bank's balance sheet characteristics including Bernanke & Gertler (1995), Kashyap & Stein (2000), Jiménez et al. (2012). This paper uses a bank's pre-regulation balance sheet strength measured by capital for a policy change to have a differential impact on banks' liquidity drainage and lending. Second, it also relates to other research work that examines non-conventional monetary policies that become prevalent in developed countries during financial crises to affect loan supply and economic activities. Ananou et al. (2021) examine the impact of the 2003 liquidity regulation on Dutch banks in the Netherlands on bank lending in Europe. Banerjee & Mio (2018) looked at the causal effect of the 2010 liquidity regulation on banks' balance sheets in the UK. Bowman et al. (2011) analyze Japan's "quantitative easing policy"(QEP) in increasing loan supply and stimulating aggregate demand. To the best of our knowledge, our study is the first to assess the bank lending channel in developing countries exploiting regulation as a natural experiment using loan-level panel data.

Third, the study also contributes to the empirical literature that uses loan-level data to assess the lending channel of monetary policy shock. Khwaja & Mian (2008) employed within-firm cross-sectional comparisons of bank lending behaviors and used loan-level data to show the impact of a liquidity shock on lending. Jiménez et al. (2012) use the same approach for different types of loans and show that higher interest rates reduce the granting of loans by banks with low capital or liquidity ratios. These studies, however, are based on multiple bank lending relationships and exclude the single-bank lending relationship, prevalent in developing countries like Ethiopia. Degryse et al. (2019) show that firms with multiple lending relationships tend to be older and more capital-intensive than those with single relationships. Firms in developing countries, in general, tend to be small and credit-constrained. The generalizability of the results based on single-bank credit relationships for developing countries is thus in question. To overcome this problem the data are constructed at firm-cluster as in Abuka et al. (2019) where a firm cluster includes all firms in a given region and industry. So, the treatment effect is obtained by comparing changes in the loan supply within the firms-cluster from the two groups of banks before and after implementation of the regulation as in Khwaja & Mian (2008).

Finally, the study adds to the literature that studies the same regulation. Limodio & Strobbe (2023) model the regulation as an increase in bank liquidity and examine its impact on loan supply over two years. Yet, such treatment of the regulation is contrary to the NBE definition of liquid assets and banks' treatment of NBE bill as a long-term investment. The approach in this paper is different from Limodio & Strobbe (2023) in four ways: the treatment of the regulation, the identification strategy, the event window, and the type of data used. This study considers the regulation as a tax on banks that leads to liquidity drainage such that it can be considered as a contractionary monetary policy. The result conflicts with what Limodio & Strobbe (2023) found and confirms the prevalence of bank lending channels. The regulation is used as an instrument to raise government revenue (Limodio & Strobbe 2016) to finance short-term government deficits (IMF 2018, 2013). The risk diversification theory argues that government borrowing might induce banks to undertake relatively more risky private lending that would increase their total lending. (Kumhof & Tanner 2005). This study shows that the above predictions did not hold in Ethiopia during the study period since the average loan size that banks originated declined. The rise in the total volume of loans in the short event window simply indicates how the bank's balance sheet strength determines loan supply.

## 3.2 Context

Following the overthrow of the Marxist Derg regime in 1991, the new government led by the Ethiopian Peoples' Revolutionary Democratic Front (EPRDF) implemented a Structural Adjustment Program (SAP) to restore the economy ravaged by war. The program aimed to encourage the development of the private sector, foster competition throughout the economy, and promote the market determination of all prices, including the exchange rate and interest rate AfDB (2000). One of these reforms was to restructure the NBE to fit into the market-based economic system. The new Banking and Monetary Proclamation No. 83/1994 allowed the establishment of a private financial institution and ended the government monopoly on the financial sector, which was in place for almost two decades. The proclamation redefined the authority of the NBE and provided the Bank with the authority to regulate and supervise the banking sector. Under the new proclamation, the Bank is entrusted with the objective of achieving monetary stability, stable exchange conditions, a sound financial system and promoting a balanced growth of the economy.

The government's role in the economy was not completely abandoned, however. The National Bank of Ethiopia supported government economic policies through direct advances to the government, which were limited to 25% of government revenue for the preceding three budget years. The government's role and participation in the economy were laid down in its five-year development strategies. In 2001, Ethiopia formulated and implemented a comprehensive Industrial Development Strategy (IDS) that was aligned with the first broad Agricultural Development Led Industrialization (ADLI) strategy. The government incorporated the IDS into its subsequent five-year development plans and continued to provide various fiscal and financial incentives to investors. To finance large public investment projects in selected priority sectors, the government sought additional financing beyond the traditional direct advances from the NBE.

The Ethiopian banking sector was long characterized by excess liquidity due to a stringent loan approval process with high collateral requirements. In March 2011, the excess liquidity of the banking sector was Birr 23.2 billion, 43% above the required liquidity level. So, the government decided to raise the required funding from the banking sector. However, the monetary policy instruments available to the NBE fell short of its objectives. For almost two decades since the private sector was allowed to participate in the banking sector, the NBE has used reserve requirements and liquidity ratios as monetary policy instruments to affect banks' liquidity position and credit supply. Moreover, monetary authorities often resort to regulatory measures like determining the minimum deposit interest rate and a credit cap to manage the credit supply and the economy.

To finance the government-funded development projects, the NBE issued a new directive on the Establishment and Operation of the NBE Bill Market: MFA/NBEBILLS/001/2011. The regulation states that all banks should participate in the financing of priority sector development projects to bring sustained economic development. The directive was announced at the end of March 2011 and became effective the next month. The directive requires all 14 commercial banks except the Commercial Bank of Ethiopia (CBE), a state-owned bank that accounted for 39 % and 30% of the banking sector capital and branch network in 2011, to allocate 27% of their new loan disbursement to buy NBE bill. The return on the investment was 3%, which is lower than the 5% minimum deposit interest rate determined by the government and matures after five years. The justification put forward by the authorities for the exclusion of the CBE was that the bank was already financing many development projects through State Owned Enterprises (SOEs). In April 2011, CBE's outstanding loan for SOEs stood at Birr 7.9 billion and accounted for 31% of its total outstanding loans. Though new entrants to the banking sector were subject to the regulation, they were excluded from the analysis.

The absence of an interbank market and access to international capital could exacerbate the impact of the regulation on access to credit. Though the interbank lending market was in its infancy, the regulation did not exempt it and contributed to its demise restricting banks' access to short-term financing. The regulation allows banks to pledge the NBE Bill as collateral to borrow from the central bank. However, it does not specify the conditions under which banks can borrow from the central bank using the bill as collateral. The absence of a capital market also made it impossible for banks to access short-term financing against their investment in NBE bills to ease the liquidity pressure. Following the regulation, banks experienced a fall in liquidity. Ten months after the policy change, the banking sector liquidity (excluding the CBE) declined by 23 percentage points from 64.7% in March 2011 to 41.7% in February 2012. To mitigate this liquidity drainage, the central bank reduced banks' reserve requirement (RR) and liquidity requirement (LR) in January 2012, 10 months after implementing the policy change, from 15% and 25% to 10% and 20%, respectively. The Bank further reduced the RR to 5% in March 2013. Experts in the financial sector (Tesfaye 2019) including the IMF (see, IMF 2018, 2013) argued that the regulation is financial repression and crowds out private-sector lending and investment.

## 3.3 Data source

The study uses two confidential data sources obtained from NBE. The first is the balance sheet data of 14 commercial banks that were operational and subject to the regulation. The data contains detailed monthly asset and liability side information including the capital, asset, and liquid asset and its components. The bank's balance sheet also reports the amount of NBE bill each bank purchased monthly. The balance sheet data are used for the identification strategy and to understand the transmission mechanism of the liquidity shock. The second data source is the credit register database. Ethiopia has a fully functioning and comprehensive credit register database procured from Compu Scan Direct Credit Bureau Solution but owned and maintained by the Credit Register Bureau (CRB) of the NBE. The credit register database was set up in 2008 and collects data on all loan applications and outstanding loans based on monthly reports from all commercial banks. The credit register database is continuously updated to improve its quality and meet regulatory objectives of the NBE.

Banks report separate data files to the CRB on loan applications and outstanding loans. The CRB thus has two different supervisory datasets with no restriction on the minimum size of the loan. The period of analysis in this study covers 20 months, from June 2010 until January 2012, which is 10 months before and after the implementation of the policy change. The post-regulation period is also extended by four months to see the impact of the regulation on the longer event window. The two data sets have unique borrower IDs assigned by the NBE and application data. Though it is possible to trace loan applications in the outstanding loan dataset (and vice-versa) by a bank, more than 87% of applied loans in the loan application dataset during the sample period do not have unique borrower IDs. Therefore, I looked at the two datasets separately. The loan application data for each bank have eight loan application statuses for each loan application including approved loans and rejected loans. Yet, the number of approved and rejected loans in the sample period turned out to be very small, with 96 observations only. I, therefore, used the outstanding loans data file only to understand the impact of the policy change on both the intensive and extensive margins of lending.

The loan-level data contains loans to financial and non-financial borrowers, but the study focuses on loans to non-financial institutions. The unique borrower ID allows us to track borrowing over time and across banks. When a borrower has more than one loan of the same type in the same bank and the same month, we add up these loans and consider them as one loan. In the sample period, there are a total of 22,144 outstanding loans from 17,270 borrowers. All loans are expressed in the Ethiopian local currency, Birr (ETB). Each outstanding loan has the amount of loan requested and approved loans, its maturity, repayment frequency, location by region (11 regions), and sector of activity (7 industries), but no interest rate information on the loans. More than 94% of the borrowers in our sample period are individuals (non-incorporated businesses). Borrowers' balance sheet information is, however, not included in the credit register database. As a result, investigating the impact of the regulation on business performance is impossible. The data set shows the prevalence of single-bank relations in the banking sector, where 91.4% of firms have an outstanding loan only from one bank, and 8.6% from more than one bank. This makes the use of a within-firm (borrower) comparison of the change in loan supply between the two groups of banks impossible. So, the data are set up at the bank-firm cluster-month level where the cluster includes all firms in a given region and industry (for a total of 43 region-industry pairs).

Table 3.1: Summary statistics

| Variables | Observation | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Panel A: Bank's Balance Sheet aggregates | | | | | |
| NBE bills | 331 | 5.56 | 4.94 | 0.00 | 12.63 |
| Cash-on-hand | 331 | 5.23 | 0.53 | 3.86 | 6.07 |
| Treasury bills | 331 | 1.48 | 0.83 | 0.43 | 3.20 |
| Deposit with banks | 331 | 21.91 | 2.20 | 17.32 | 25.13 |
| Liquid assets | 331 | 39.74 | 4.38 | 31.25 | 45.58 |
| Liquid assets minus reserve | 331 | 28.62 | 2.51 | 23.99 | 32.03 |
| Capital | 331 | 0.38 | 0.26 | 0.08 | 0.98 |
| Panel B: Credit Register aggregates | | | | | |
| ln(Total loan) | 2,502 | 8.02 | 1.94 | 0.00 | 12.72 |
| ln(Average loan) | 2,502 | 6.48 | 1.51 | 0.00 | 9.10 |
| ln(Repayment period) | 2,502 | 1.03 | 0.44 | 0.00 | 2.56 |
| ln(Number of loan) | 2,502 | 1.64 | 0.10 | 0.69 | 5.36 |

*N.B.:* This table set out the summary statistics for the main variables we use in the analysis. The bank-level variables in Panel A come from the banks' balance sheets and are presented in Billions of Ethiopian currency, ETB. Panel B presents the summary statistics for variables from the Credit Register database and is expressed in natural logarithm, where the data are aggregated at the bank-firm cluster-month level, where a cluster includes all firms in a region-industry pair (see Section 4.1 for details). Approved loans indicate the number of outstanding loans while the maturity period and payment frequency are the loan maturity and repayment period expressed in months. The average loan repayment period is 2.1 months and the period of the analysis is from June 2010 to January 2012.

Table 3.1 provides summary statistics on the key variables used in the analysis. On average banks purchased ETB 5.4 Billion worth of NBE bills each month, more than the average cash holdings of banks which stood at ETB 5.2 Billion. The summary statistics also show that banks hold a significant amount of liquid assets as deposits with other banks, which accounts for 55% of total bank liquid assets.

Figure 3.1: NBE-Bill

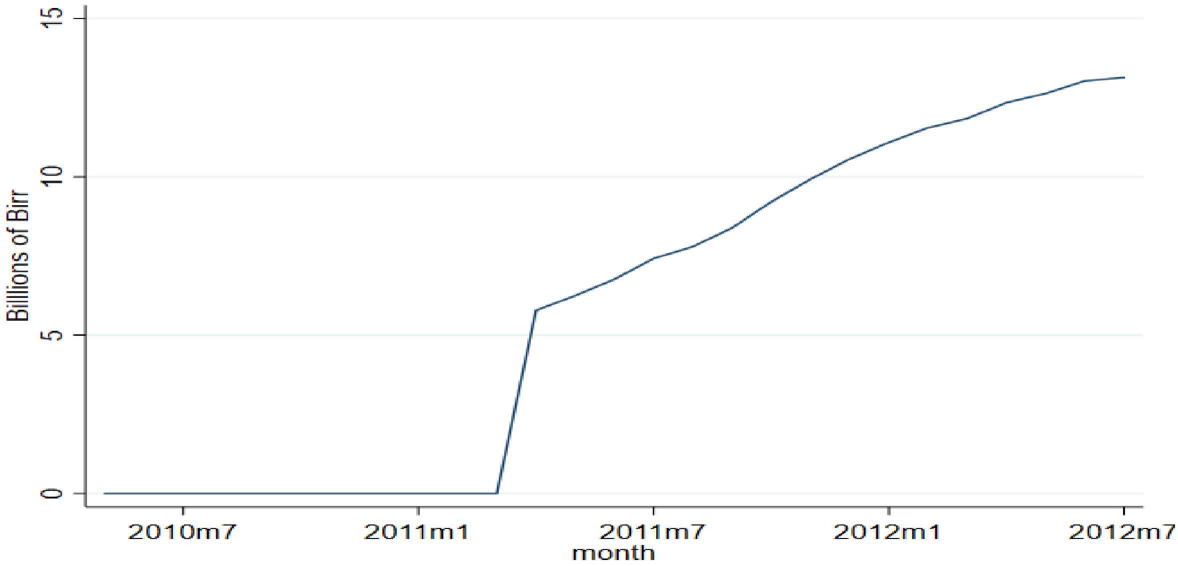
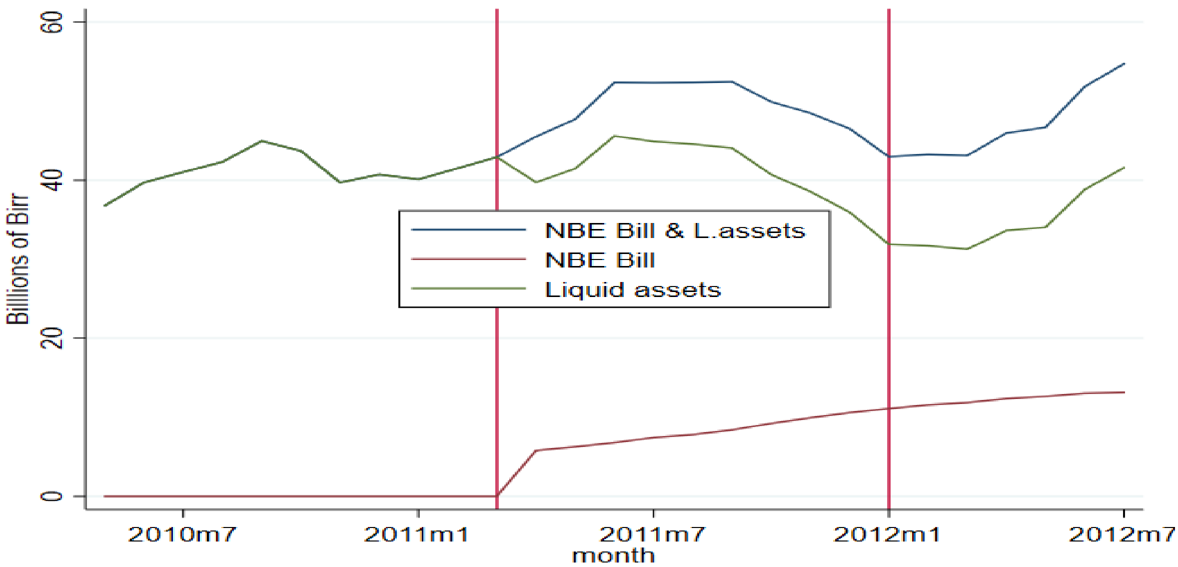
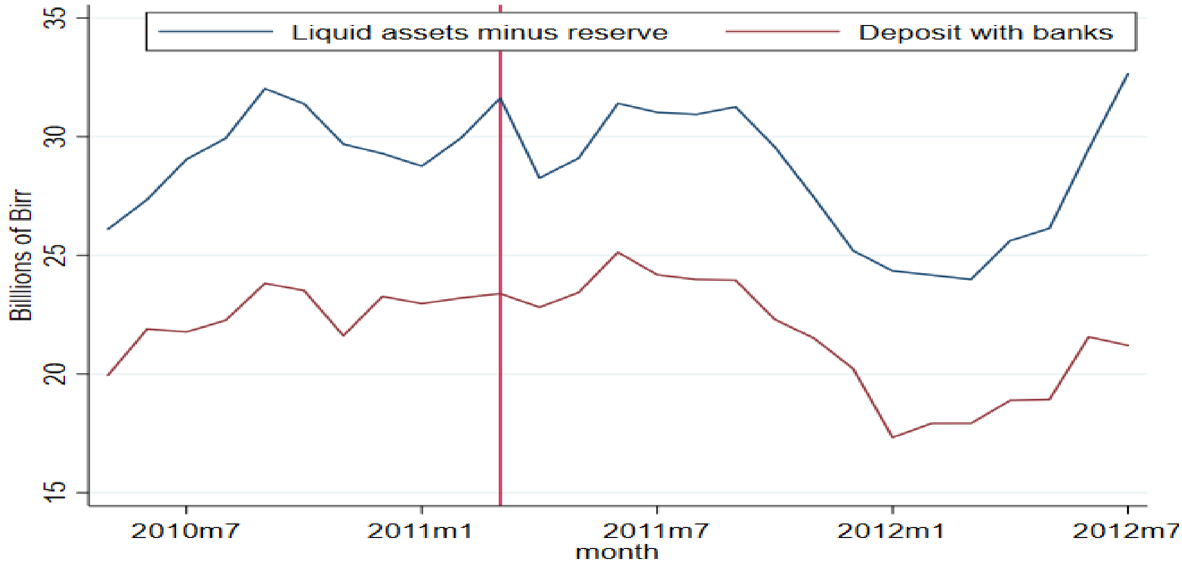



Figure 3.2: Liquid asset




N.B.: Figure 3.1 shows the total NBE bills that banks purchased from April 2011 to July 2012 while Figure 3.2 indicate the total banking sector liquidity and the total banking sector liquidity minus reserves, which is the sum of NBE bills and total liquidity. The first and second vertical lines respectively show April 2011 when the policy was introduced and January 2012 when a new policy reducing reserve requirement and liquidity ratio was introduced.

Figure 3.3: Total liquidity minus reserves

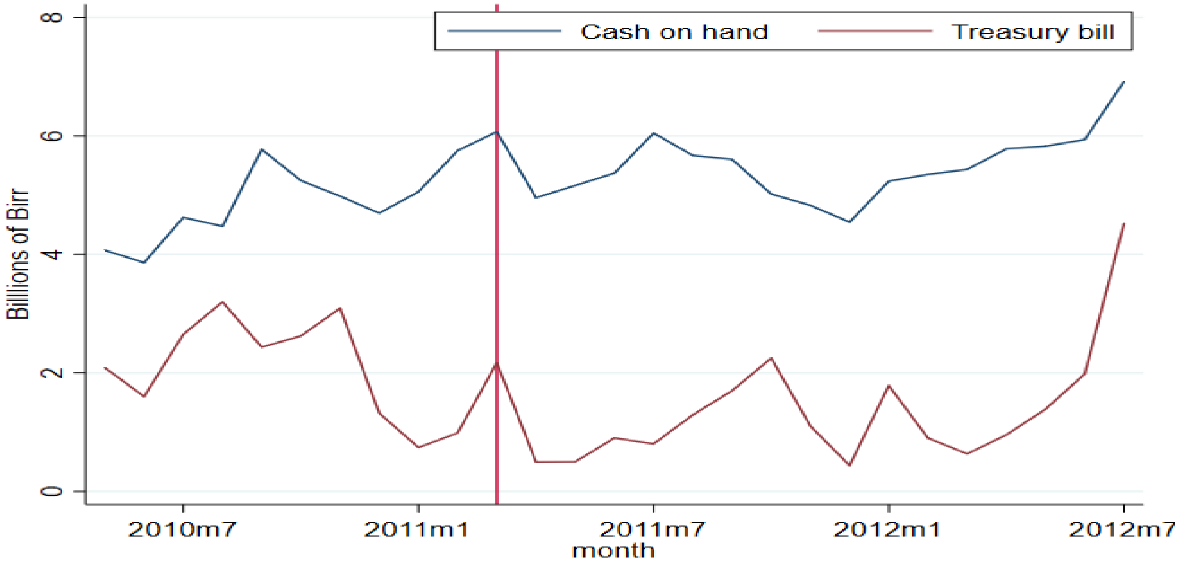



### 3.3.1 Descriptive statistics

This subsection presents descriptive statistics and the behavior of private banks, exploiting the introduction of a new mandatory regulation announced at the end of March 2011 and implemented on April 4, 2011. Figure 3.1 presents the total volume of NBE bills that banks purchased in each month after the implementation of the regulation. The figure indicates that in the first month of the implementation of the regulation, banks purchased a total of ETB 5.7 Billion worth of NBE-Bill. This amount reached ETB 11.8 Billion after a year in March 2012. This amount is equivalent to 1.2 times the total capital of all commercial banks, which stood at ETB 10.6 Billion, and suggests how instrumental the regulation was in raising government revenue. A counterfactual estimate by Limodio & Strobbe (2016) shows that the policy generated revenue that lies between 1.5% and 2.6% of the total tax revenue, corresponding to 20% of all Personal Income Tax revenue.

The regulation likely created a liquidity shock affecting banks' liquidity, which is comprised of cash on hand, deposits with other banks, Treasury bills, and reserves with the NBE. Figure 3.2 presents the banks' total liquidity and shows that liquidity started to decline immediately after the regulation. Though it improved for the next two months, it started to decline in July 2011 and continued to decline for the next nine months until March 2012, which is exactly one year after the regulation was introduced.

Figure 3.4: Cash and Treasury bill




N.B.: Figure 3.3 shows the total liquidity minus the mandatory reserve that banks are required to hold with the central bank. Figure 3.4 shows cash on hand and Treasury bills.

The total liquidity presented in Figure 3.2 includes the mandatory legal reserve requirement and may hide the banks' response to the policy change. To provide a comprehensive overview of the changes in banks' liquidity, Figure 3.3 shows the liquidity minus this mandatory reserve requirement, and the other components of liquidity. Looking at the components of liquidity, it is clear that both bank-to-bank deposits (Figure 3.3) and cash on hand- the most liquid asset (Figure 3.4), underwent a similar decline after the implementation of the regulation. But, the decline in bank deposits is more pronounced than the cash on hand and drives the decline in total liquidity. Yet, this analysis is insufficient to ascribe the preceding result to the regulation and infer a causal impact. Section five looks at the causal impact of the regulation on liquidity as a transmission mechanism.

## 3.4 Identification

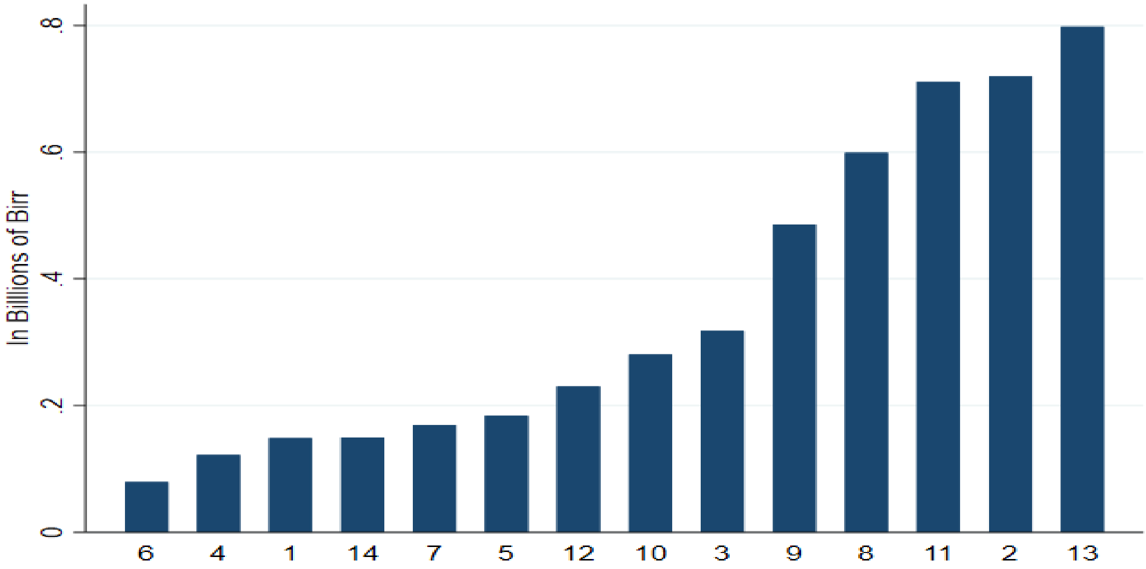
The empirical problem in the bank lending channel is the identification issue because banks' lending is endogenous to both their lending policies and borrowers' credit demand shock. Banks experiencing a liquidity shock might be lending to firms whose demand for a loan has declined. Besides, the indiscriminate application of NBE bills regulation further complicates the identification strategy in assessing its impact on banks' lending behavior. The sudden announcement and immediate implementation of the regulation, however, exposed banks to a differential liquidity shock that can be used as an identification strategy. Kashyap & Stein (1994) shows that large banks with more loanable funds are less sensitive to changes in monetary policy, and support loan growth. More capitalized banks can attract deposits and market funds on better terms than other banks (Bernanke 2007, Gambacorta & Shin 2018), suggesting that the impact of liquidity shock on lending depends on a bank's balance sheet strength.

I assume that the pre-regulation cross-sectional variation of the bank's capital was exogenous to the regulation, and exploited it for identification strategy. This study used the pre-regulation bank's median capital in March 2011 to group banks into two cohorts: less-capitalized and more-capitalized banks. Figure 3.5 presents the distribution of the pre-regulation bank's capital in March 2011. The hypothesis is that more capitalized banks - banks with above the median capital before the policy change - were more liquid, had more loanable funds, used to lend more, and will continue lending more in the short run compared with under-capitalized banks. Since banks are required to allocate 27% of their new gross loan disbursement to buy NBE bills, banks that continue lending after the policy change will eventually experience larger liquidity drainage and less lending in the relatively long period compared to smaller banks.[2] So, smaller banks are used as a control group to estimate the counterfactual.

The identification in this paper is similar to the one used by Bentolila et al. (2018), Carletti et al. (2021), Khwaja & Mian (2008) in the sense that banks are grouped based on their differential exposure to exogenous liquidity shocks. As Abuka et al. (2019) noted for Uganda, however, the prevalence of single-bank credit relations in the Ethiopian banking sector is also substantial. In the event window, which spans between May 2011 and January 2013, only 8.6% of borrowers have loans from two banks. This makes the use of a within-firm comparison of the change in loan supply between the two groups of banks impossible. So, the data are set up at the bank-firm cluster-month level where a

[2]The test for this hypothesis is presented in Figure C.1.

Figure 3.5: Pre-regulation bank's Capital




Note: Figure 3.5 shows the capital of all banks subject to the regulation, one month before the introduction of the policy.

firm cluster includes all firms in a given region and industry. So, the identification of treatment is obtained by comparing changes in the loan supply within the firms-cluster from the two groups of banks before and after the implementation of the regulation as in Khwaja & Mian (2008).

I estimate the following event study equation to identify the causal impact of the regulation on the bank's loan supply:

$$(Y)_{bct} = \alpha_b + \phi c + \gamma_t + \sum_{k \neq -1} \beta_k \times 1(D^k_{bct}) + \varepsilon_{bct} \tag{3.1}$$

where $Y_{bct}$ is an outcome variable for bank $b$, firms-cluster, $c$, at month $t$, and measures the intensive and extensive margin of lending. For the intensive margin, we use, log (Total loan) and log (Average loan) from a bank to a firm-cluster in each month. The extensive margin of lending is measured using the log (Repayment period) and log (Number of loans). $D^k_{bct} = T_{bc} \times 1(t = k) = 1$, if a loan was disbursed to a firms-cluster, $c$, by the bank, $b$, that was treated (large banks) $k$ months ago, $T_{bc}$ denotes a treated bank, $b$, lending to a firm-cluster, $c$. The equation includes bank fixed effects $\alpha_b$, time fixed effects, $\gamma_t$, and cluster fixed effects $\phi_c$. The time-fixed effect controls for the overall time trends. The bank-fixed effects capture time-invariant heterogeneity across banks while the cluster-fixed effect controls for cluster heterogeneity. I also include time-varying fixed effects at the cluster level, using cluster $\times$ month fixed effects to control for the change in credit demand by cluster over time,

In our setting, assignment to the treatment occurs at the bank. Thus, the standard errors are first clustered at the bank level, However, the number of banks is small, just 14. The study thus uses wild bootstrap as recommended by Cameron et al. (2008) to construct robust standard errors.[3] I also estimate the event study coefficients using the High Dimensional Fixed Effect(HDFE) estimators. HDFE allows for two or more levels of fixed effects and clustering. The coefficient estimates and bootstrapped standard errors from OLS regression for the liquidity and loan equation are similar to the coefficient estimates using one-way clustered standard errors from HDFE regression and they are presented in Table C.1 to Table C.5.

The loan-related variables are, however, constructed at the industry-region cluster. Thus the results reported, and the sensitivity analysis in this analysis are based on the HDFE estimation method for it allows multiple fixed effects and clustering. The standard errors are therefore clustered both at the bank and the cluster levels to overcome the problem of serial correlation of the outcome variables by treatment group and cluster. The above event study equation without cluster fixed effect is also estimated for bank-level variables measuring banks' total liquid assets and its components: ln(Liquid asset), ln(Cash on hand), and ln(Deposit with banks).

One important question in impact evaluation is the choice of event windows. Miller (2023) suggested the importance of using a judgment call in the choice of the event window and reference period. The choice of the event window in this analysis is, therefore, determined by two factors. The first is the ability of banks to change their liquidity position in response to the policy change. In the absence of a short financing facility and access to foreign capital markets, the only viable solution to ease the liquidity drainage was branch expansion to mobilize deposits and raise liquidity. To mitigate the impact

[3] We use the ***boottest*** Stata routine developed by Roodman et al. (2019) to cluster robust standard errors.

of the liquidity shock, banks expanded their operations to the unbanked areas of the country. Seven months after the introduction of the directive, the three better-capitalized banks opened 15 branches. However, raising enough deposits to help mitigate the liquidity drainage induced by the policy change may take longer. The Second factor is NBE policy measures in the subsequent months. To mitigate the liquidity drainage induced by the policy change, NBE reduced banks' RR and LR respectively in January 2012. To avoid possible confounding factors, the first event window therefore includes ten months before and after the implementation of the regulation, which is from June 2010 to January 2012, and I considered this period as a short-event window.

The liquidity drainage induced by the policy change may have a relatively longer lag effect to affect banks' lending behavior. Ten months after the regulation could therefore be relatively short for the policy change to have an impact on banks' loan supply. In addition, the loans that banks report to the Credit Register Bureau of the NBE each month are loans that were dispersed some months before and started to be paid back. As a result, outstanding loans reported for the first few months after the implementation of the regulation may not truly capture the effect of the regulation on banks' lending behavior. The reduction in RR and LR in January 2012 could also have a lag effect due to the outstanding loan reporting system. So. restricting the post-regulation period to 10 months may mask the long-run effects of the regulation. For the same reason, the second policy change introduced in January 2012, will have the same large lag effect. I. therefore, extend the post-regulation period to 14 months, until May 2012 to examine the long-run effect of the policy change, where the second policy changes are not expected to have an effect.

The fact that banks are grouped into treated and control groups based on the differential liquidity shock (intensity of treatment) which depends on the bank's capital position may raise a natural challenge in the identification strategy. The two groups of banks could have been different in their ex-ante characteristics and could have evolved differently in the absence of the policy change. I thus undertake a test for parallel trend assumption for a set of observable indicators of bank characteristics, particularly on banks' total as-

Figure 3.6: Total asset

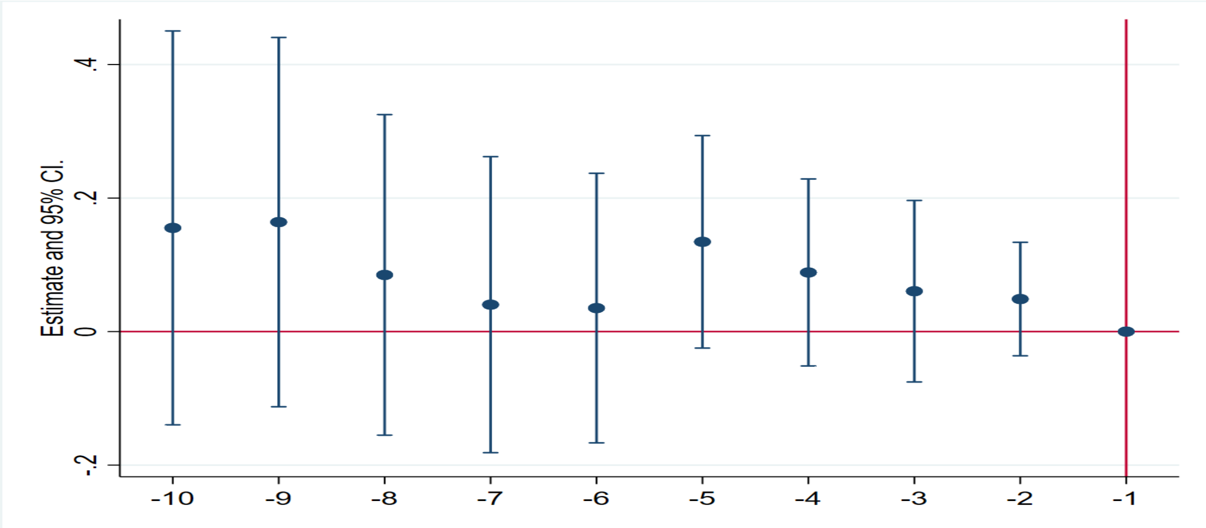
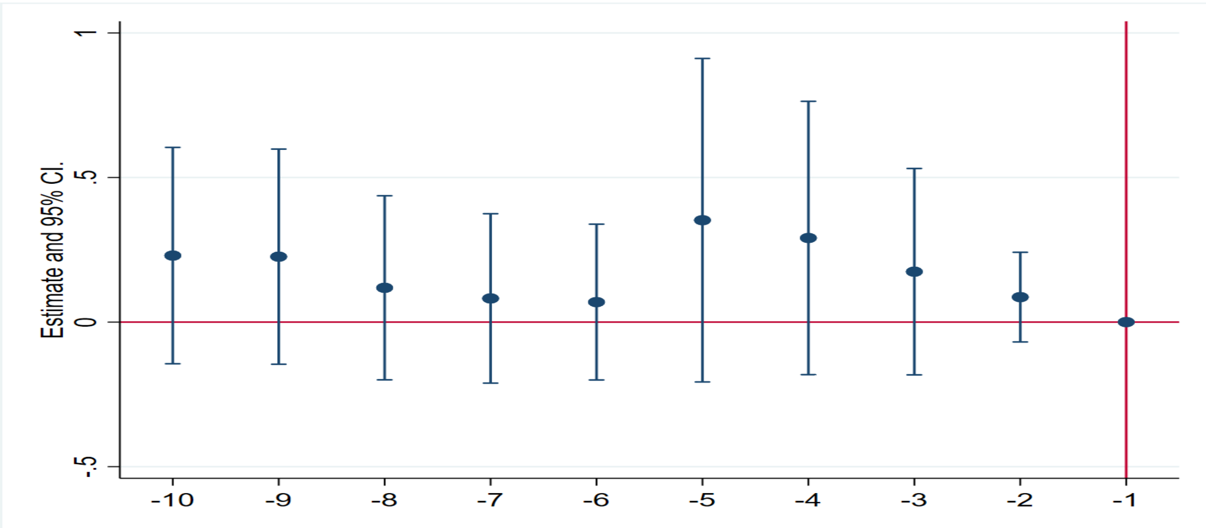



Figure 3.7: Deposit




Note: Figure 3.6 and Figure 3.7 show pre-trends for the natural logarithm of banks' total capital and total deposit from equation (1). Each monthly observation is a bank-level with $N = 331$. Standard errors are clustered at the bank level.

sets Figure 3.6 and deposits Figure 3.7. The pre-trend tests for total asset and deposits for the two groups of banks show that $\beta_k = 0$ for all $k < 0$ from equation (1) is not statistically different from zero. So, the hypothesis that $\beta_{pre} = 0$ can not be rejected, and confirms the validity of the identification strategy. Further pre-trend tests for other observable characteristics of banks such as the bank's total liability Figure C.2, and total capital Figure C.3, both expressed in logarithmic, confirm the validity of the identification strategy.

## 3.5 Results

If the introduction of the NBE-bill regulation had an impact on bank lending behavior, this effect has to come through liquidity drainage. Therefore, this study first explores the impact of the regulation on bank liquidity and estimated equation (1) when the dependent variable is total liquidity and its component without the cluster fixed effects. The study then investigated whether banks transmit liquidity shock to borrowers to understand the existence of bank lending channel in developing countries. In both cases, the estimation is undertaken for two event windows to capture the effect of the policy change both in the short and long event windows. All estimated coefficients are based on multi-level fixed effects(HDFE) regression where standard errors are clustered both at the bank and cluster levels.[4]

### 3.5.1 The effect of the regulation on bank liquidity

This section explores the effect of the policy change on banks' liquidity to understand the transmission mechanism of the bank lending channel. The purchase of the NBE bills depends on the amount of loans that each bank originates, which in turn depends on the bank's financing ability or the availability of loanable funds. The attachment of the policy to loan disbursement affects the bank's liquid assets. The event study model presented in equation (1) is thus first estimated using OLS and HDFE estimation methods for banks' liquid asset and its components both in the short and long event window. The coefficient estimates and the bootstrapped clustered standard errors from OLS regressions for both event windows are very similar to the HDFE regression when the standard errors are clustered at the bank level (see, Table C.1 for the longer event window). As a result, I used the result from HDFE regression for it absorbs multiple fixed effects and clustering.

Table 3.2 presents the post-regulation event study coefficient estimates. The regression includes bank, month fixed effects, and cluster X month fixed effects. The first three columns are based on the event windows where the post-regulation period is restricted to 10 months. Column(1) indicates that the total liquidity of better-capitalized banks

[4]The model is estimated using Clarke & Tapia-Schythe's (2021) *eventdd* Stata command.

started to decline beginning from the sixth month when total liquidity fell by 26.1%. In the tenth month, the effect stood at about 53%. These effects are significant at a 5% significance level. For the cash-on-hand, given in column(2), however, the regulation had an immediate and significant impact starting from the first month. This negative effect is prevalent and significant in all post-regulation months. In the tenth month, the policy change reduced the cash of better-capitalized banks by 128.2% compared to the comparison group. The result is consistent with the hypothesis that the regulation can lead to banks' liquidity drainage. Column(3), on the contrary, shows that the regulation did not affect banks' deposits with other banks in any of the first ten months of the post-regulation period. The lack of significant negative effect on deposits with other banks could be because banks keep such deposits for payment and settlement purposes and it is not directly related to bank lending in the short event window.

Columns (3) to column (6) of Table 3.2 present the result when the post-regulation period is extended to 14 months. The results indicate that restricting the post-regulation period to 10 months masks the long-run effect of the policy change on banks' liquidity. Column (4) indicates that the liquidity drainage continued until the $13^{\text{th}}$ month of the post-regulation period. In the $11^{\text{th}}$ month, the total liquidity of more capitalized banks' declined by 59.4% compared to under-capitalized. The effect becomes 54.3% in the $12^{\text{th}}$ month and reaches 57.1% in the $13^{\text{th}}$ month, which are both significant at a 5% significance level. For cash-on-hand, the effect of the regulation continues to be negative, and significant in the long run as well. Similarly, for Bank deposits, the regulation seems to have an effect in the long run as the coefficient estimates turn out to be negative and significant in the $11^{\text{th}}$ and $13^{\text{th}}$ months.

These results are unbiased if the parallel trend assumption holds. The coefficient estimates before the implementation of the policy change for total liquidity (Figure 3.8), cash-on-hand (Figure 3.9), and deposit with other banks (Figure C.4) are all statistically not different from 0 confirming that the pre-trend holds.[5] Using the traditional approach, we can conclude that the policy change led to liquidity drainage of better-capitalized banks

[5]The pre-regulation coefficient estimates based on the short event window (not shown) leads to the same conclusion.

Table 3.2: Impact of the policy change on bank liquidity

| | Short-term | | | Long-term | | |
|---|---|---|---|---|---|---|
| | (1) Liquid asset | (2) Cash on hand | (3) Bank depost | (4) Liquid asset | (5) Cash on hand | (6) Bank depost |
| 1st Month | -0.027 | -0.298** | 0.103 | -0.027 | -0.298** | 0.103 |
| | (0.067) | (0.111) | (0.077) | (0.067) | (0.111) | (0.077) |
| 2nd Month | -0.117 | -0.403** | 0.031 | -0.117 | -0.403** | 0.031 |
| | (0.088) | (0.158) | (0.097) | (0.088) | (0.158) | (0.097) |
| 3nd Month | -0.130 | -0.482** | 0.031 | -0.130 | -0.482** | 0.031 |
| | (0.100) | (0.173) | (0.102) | (0.100) | (0.173) | (0.102) |
| 4th Month | -0.168 | -0.472*** | -0.033 | -0.168 | -0.472*** | -0.033 |
| | (0.105) | (0.152) | (0.100) | (0.105) | (0.153) | (0.100) |
| 5nd Month | -0.243** | -0.516** | -0.126 | -0.243** | -0.516** | -0.126 |
| | (0.107) | (0.172) | (0.099) | (0.107) | (0.172) | (0.100) |
| 6th Month | -0.232** | -0.478** | -0.124 | -0.232** | -0.478** | -0.124 |
| | (0.096) | (0.182) | (0.094) | (0.096) | (0.182) | (0.094) |
| 7th Month | -0.309** | -0.662*** | -0.222 | -0.309** | -0.662*** | -0.222 |
| | (0.127) | (0.219) | (0.130) | (0.127) | (0.219) | (0.130) |
| 8th Month | -0.369* | -0.704** | -0.232 | -0.369* | -0.704** | -0.232 |
| | (0.173) | (0.287) | (0.147) | (0.173) | (0.287) | (0.147) |
| 9th Month | -0.418** | -0.692** | -0.178 | -0.418** | -0.692** | -0.178 |
| | (0.166) | (0.280) | (0.165) | (0.166) | (0.280) | (0.165) |
| 10th Month | -0.429** | -0.825*** | -0.175 | -0.429** | -0.825*** | -0.175 |
| | (0.169) | (0.258) | (0.173) | (0.169) | (0.258) | (0.173) |
| 11th Month | - | - | - | -0.466*** | -0.791*** | -0.239* |
| | | | | (0.141) | (0.262) | (0.129) |
| 12th Month | - | - | - | -0.434** | -0.718** | -0.228 |
| | | | | (0.184) | (0.291) | (0.174) |
| 13h Month | - | - | - | -0.452** | -0.729** | -0.292** |
| | | | | (0.159) | (0.304) | (0.123) |
| $N$ | 275 | 275 | 275 | 359 | 359 | 359 |
| Adj. $R^2$ | 0.981 | 0.918 | 0.976 | 0.973 | 0.896 | 0.969 |

N.B.: The table shows post-regulation monthly estimates from the event study model of equation(1) for liquid assets and the components. All variables are expressed in a natural logarithm. The model in all regressions includes bank and month-fixed effects. The standard errors in parentheses are clustered at the bank level. *p $<$ 0.10, **p $<$ 0.05,***p $<$ 0.01

with more capital compared to smaller banks. Nonetheless, as Roth (2022) indicates, the power of conventional pre-trend tests may be low to detect important violations of parallel trend, and the analysis based on pretest result may distort estimation and inference, potentially exacerbating the bias of point estimates and result in an under coverage of confidence intervals.

A key concern in the identification strategy in this regard is that banks are grouped into treated and comparison groups based on the intensity of treatment. As a result, these two groups of banks could have different liquidity positions which could have evolved into different trends in banks' lending behavior even in the absence of the regulation.

Moreover, total liquid assets exhibit a clear downward-sloping pre-existing trend (see,

Figure 3.8: Event study coefficient estimates for ln(Liquid assets)

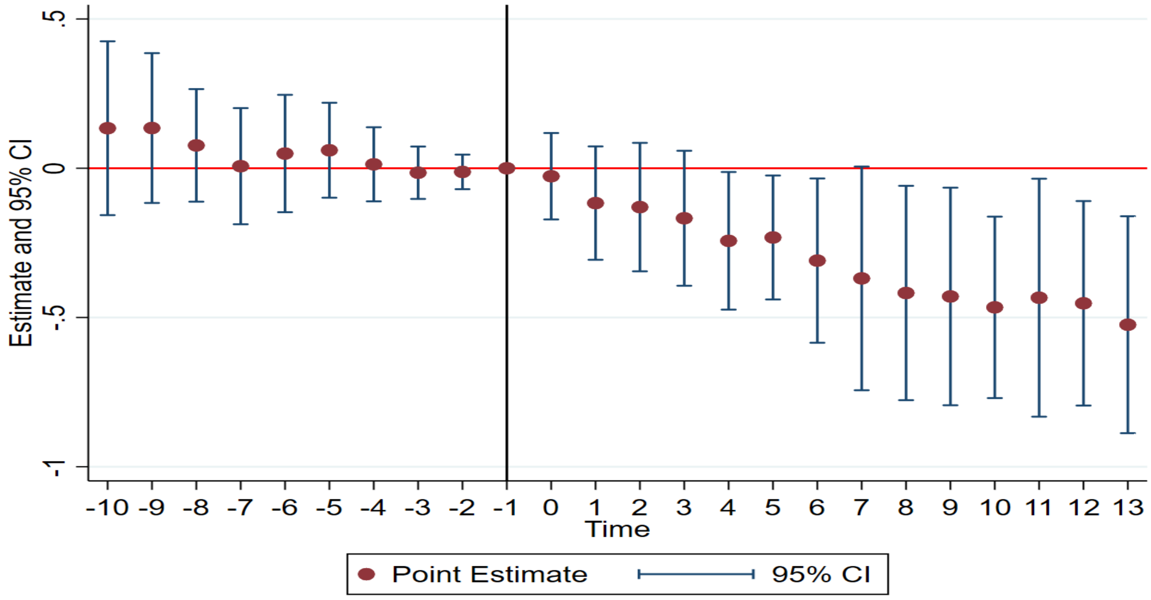



Figure 3.9: Event study coefficient estimates for ln(Cash)

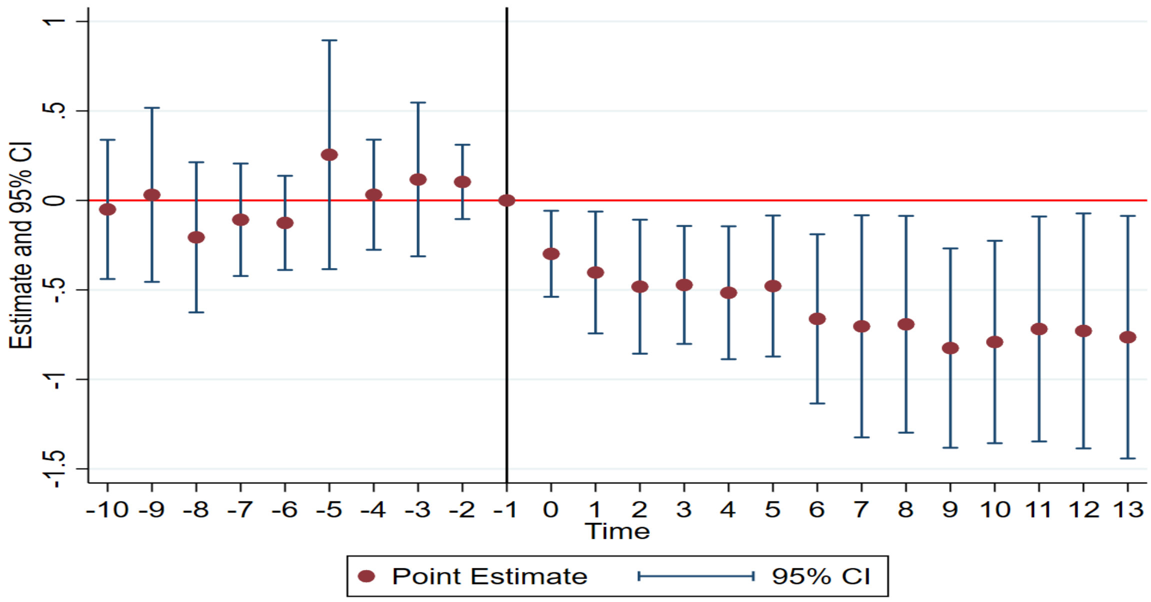



Figure 3.8). I, therefore, assume the existence of linear trends that differ systematically with treatment and are more likely to evolve smoothly over time. This assumption is based on the fact that banks' liquidity and lending activity depend on their ability to raise capital and mobilize deposits. More capitalized banks can raise capital and deposits which will increase their liquidity linearly and lead to more lending compared to under-capitalized even when the policy change was not in place. I, therefore, undertook a

Figure 3.10: Sensitivity analysis for $\beta_9$ for ln(Cash)

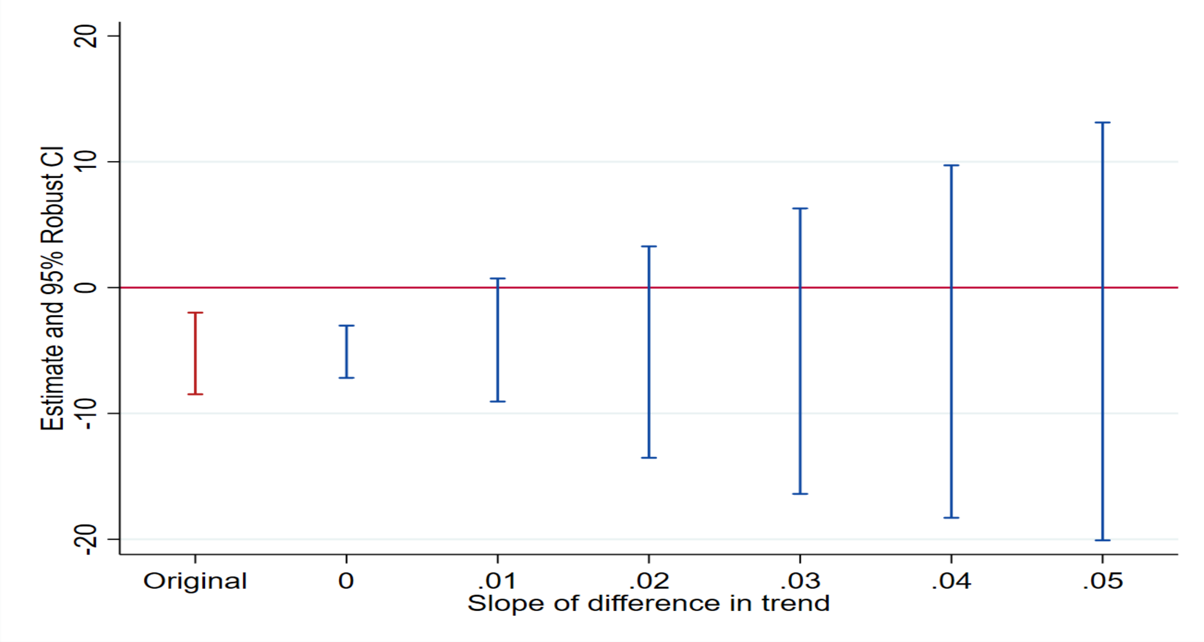
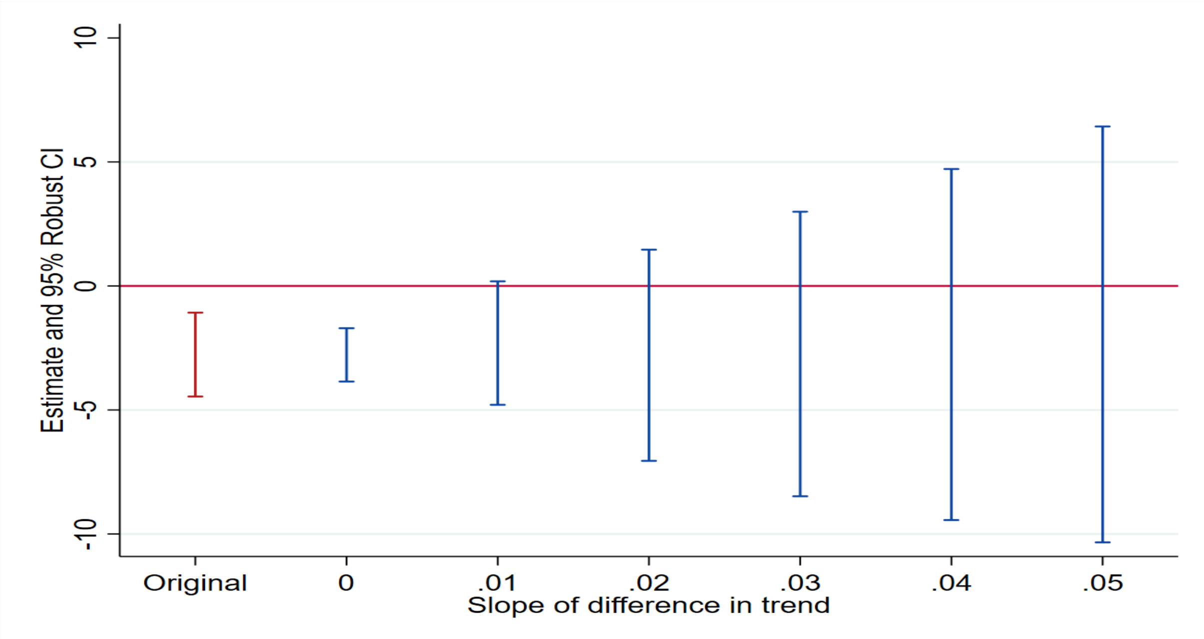



Figure 3.11: Sensitivity analysis of ATE for ln(Cash)

for over the ten months period,




sensitivity analysis as suggested by Rambachan & Roth (2023) and allowed for violation of a parallel trend that imposes smoothness linear restrictions.[6] The sensitivity analysis for the Average Treatment Effect (ATE) for $t = 10$ (Figure C.5) and the ATE over ten months (Figure C.6) shows that the robust confidence intervals include zero at a 95%

[6]I use *honestdid* Stata package developed by Bravo et al. (2022) to carry out the sensitivity analysis.

robust confidence interval. The 90% confidence interval (not shown) also includes zero, suggesting that after extrapolating the downward-sloping pre-existing trend, the result provides no strong evidence for the decline of total liquidity at the conventional significance level.

If the regulation had an impact on a bank's liquidity, it should be on cash-on-hand, the bank's most liquid asset. Figure 3.10 presents the result from the sensitivity analysis for the ATE for cash on hand for $t = 10$. The red line plots the original HDFE estimates for the tenth month. The result shows that the robust confidence set for the 10-month gets smaller and contains only negative values when allowing for violations of parallel trends that are approximately linear (M=0). When non-linearity is allowed the confidence interval becomes wider and includes zero with a "breakdown value" of M=0:01. Figure 3.11 also shows that the ATE on Cash-on-hand over ten months after imposing smoothness linear restrictions is negative and the robust confidence interval excluded zero. The result suggests that the policy change reduced the cash holding of better-capitalized banks compared to less-capitalized banks in the short event window.

### 3.5.2 The effect of the regulation on bank lending behavior

## A. Intensive margin of lending

## I. Total volume of loan

The previous analysis shows that the implementation of the policy change led to liquidity drainage of better-capitalized banks compared to smaller banks. The next question is then, Do these banks transmit this liquidity shock to their borrowers? Since the regulation is related to bank lending, the liquidity drainage could result from higher lending by treated (more-capitalized) banks in the short run. This section presents the impact of the regulation on the intensive margin of lending based on the total volume of loan supply and the average loan constructed at the firm-cluster (regions and industry) and expressed in terms of the natural logarithm. The analysis is undertaken in both two the short and long event windows separately. Table 3.3 presents the post-regulation event study coefficient estimates from equation (1) for total and average loan supply using HDFE regression for both event windows.[7] All models include bank, month, cluster, and cluster X month fixed effects, and the standard errors are clustered at bank and cluster levels.

Column (1) of Table 3.3 presents the impact of the policy change on the total volume of loan supply in the short run. The result shows that even though the regulation is attached to bank lending, better-capitalized banks continue lending in the short-run. In the first month, better-capitalized banks' loan supply increased by 118% relative to the pre-regulation month, and the effect increased to 111% in the sixth month. These effects are significant at 10% significance level. Though the other regression coefficients in the short run were positive, none of them were significant. However, this result is unbiased only if the parallel trend assumption holds. Figure 3.12 presents the event study coefficient estimates for the total volume of loans before the policy change and indicates that none of the pre-regulation coefficients are statistically different from 0 suggesting the validity of our identification strategy.[8] However, it is possible that the power of the pre-trend tests could be low to detect important violations of parallel trend Roth (2022). Moreover, the event study coefficient estimates do not provide the ATE of the regulation over a period. I, therefore, undertake a sensitivity analysis for the ATE of the regulation on the total volume loan supply over 10 months imposing a smoothness linear restriction.

After allowing for a violation of parallel trends that are approximately linear (M=0), the robust confidence interval (Figure 3.13) for the ATE on total loan supply for 10 months widens but contains only positive values. The 'breakdown" value of no null effect is around M=0.03. The result shows that the positive effect of the regulation on total loan supply is robust to the post-treatment violations of parallel trends which is no larger than three times the maximum pretreatment violation of parallel trends. The result confirms that the policy change increased the total volume of better-capitalized banks compared to under-capitalized banks, consistent with the hypothesis and the theoretical prediction that the impact of monetary policy depends on banks' crossectional differences in capital

[7] The coefficient estimates and the bootstrap clustered standard errors from OLS regression for ln(Total loan) and ln(Average loan) are similar to the HDFE estimates when standard errors are clustered at the bank level and presented in Table C.2 and Table C.3 for comparisons.

[8] The event study coefficient estimates for the ln(Total loan) for the short event window is presented in Figure C.7 and leads to the same conclusion.

Table 3.3: Impact on the total volume of loans and average loan supply

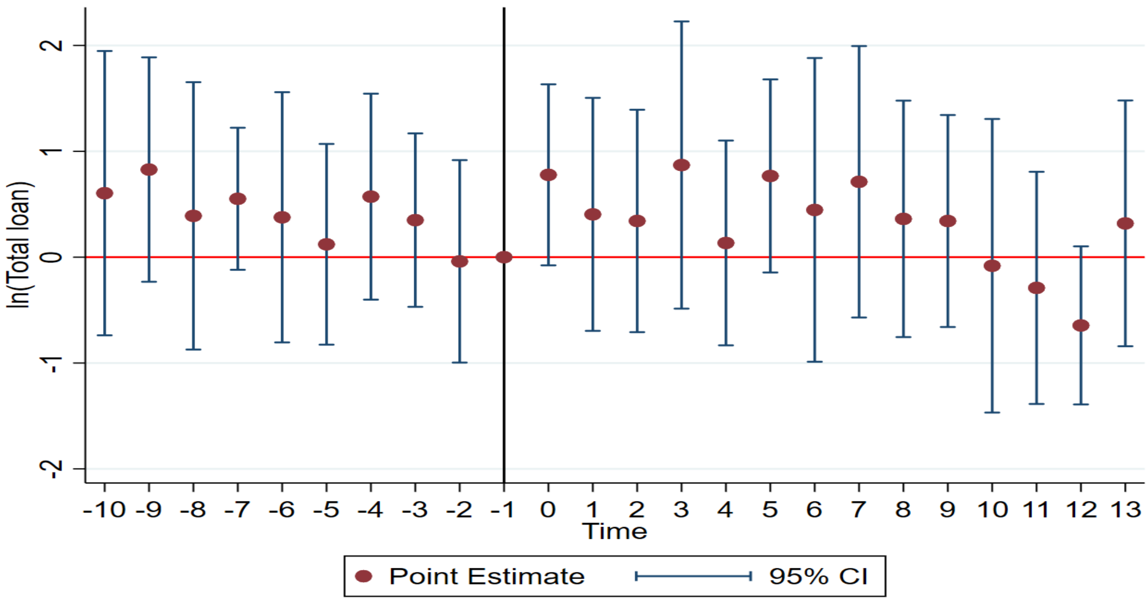
| | ln(Total loan) | | ln(Average loan) | |
|---|---|---|---|---|
| | (1) Short-term | (2) Long-term | (3) Short-term | (4) Long-term |
| 1st Month | 0.782* | 0.777* | 0.019 | 0.004 |
| | (0.401) | (0.396) | (0.262) | (0.278) |
| 2nd Month | 0.416 | 0.406 | -1.228*** | -1.243*** |
| | (0.509) | (0.510) | (0.332) | (0.344) |
| 3rd Month | 0.344 | 0.343 | -0.922** | -0.929** |
| | (0.482) | (0.487) | (0.383) | (0.381) |
| 4th Month | 0.850 | 0.870 | -0.378 | -0.378 |
| | (0.627) | (0.629) | (0.338) | (0.337) |
| 5th Month | 0.142 | 0.135 | -0.346 | -0.366 |
| | (0.439) | (0.448) | (0.289) | (0.300) |
| 6th Month | 0.747* | 0.768* | -0.289 | -0.300 |
| | (0.419) | (0.422) | (0.371) | (0.368) |
| 7th Month | 0.439 | 0.447 | -0.354 | -0.363 |
| | (0.660) | (0.664) | (0.268) | (0.273) |
| 8th Month | 0.715 | 0.713 | -0.006 | -0.006 |
| | (0.591) | (0.594) | (0.355) | (0.360) |
| 9th Month | 0.356 | 0.363 | 0.077 | 0.092 |
| | (0.508) | (0.517) | (0.280) | (0.279) |
| 10th Month | 0.318 | 0.343 | -0.240 | -0.236 |
| | (0.427) | (0.464) | (0.249) | (0.259) |
| 11th Month | - | -0.081 | - | -0.075 |
| | | (0.642) | | (0.292) |
| 12th Month | - | -0.291 | - | -0.015 |
| | | (0.508) | | (0.358) |
| 13h Month | - | -0.644* | - | -0.511 |
| | | (0.346) | | (0.399) |
| $N$ | 2295 | 2617 | 2295 | 2617 |
| Adj. $R^2$ | 0.520 | 0.507 | 0.293 | 0.289 |
| Bank FEs | Yes | Yes | Yes | Yes |
| Month FEs | Yes | Yes | Yes | Yes |
| Cluster-FEs | Yes | Yes | Yes | Yes |
| Cluster-Month FEs | Yes | Yes | Yes | Yes |

N.B.: The table shows the post-regulation monthly estimates from the event study model of equation(1). The dependent variable in columns(1) and column(2) is ln(Total loan) and it is ln(Average loan) in columns(3) and column(4). The estimate in column(1) and column (3) is for a short event wind while Column (2) and Column (4) show the result for longer event windows. The standard errors clustered at the bank level are in parentheses. *p $<$ 0.10, **p $<$ 0.05,***p $<$ 0.01.

(Kashyap & Stein 2000) and better-capitalized banks banks continue lending because of the availability of loanable funds (Kashyap & Stein 1994) in the short event window.

As indicated in Figure 3.3 and Figure 3.4, however, the banking sector liquidity excluding CBE, and its components started to decline five months after implementing the policy change and reached the minimum in the $10^{\text{th}}$ to $11^{\text{th}}$ months. Since the effect of the regulation on loan supply is expected to come through liquidity drainage, banks might not thus experience the effect of liquidity drainage in the short run. Moreover, since the average loan repayment period of the outstanding loans in the sample period is 2.1 months it is possible that bank lending in the short-run might not capture the impact of the regulation. The post-regulation period can thus be extended to include more months. The introduction of new directives in January 2012 to mitigate the liquidity problem, however, limited the possibility of extending the post-regulation period. I, therefore, restrict the post-treatment period to 13 months to examine the long-run effect of the regulation on total loan supply when the policy change is expected to affect banks' lending behavior.

Figure 3.12: Event-study coefficient for ln(Total loan) in the long run.




Column (2) of Table 3.3 presents the result for the long-term period. The result indicates that the negative effect of the regulation sets in the $11^{\text{th}}$ month and turns out to be significant at a 10% significance level in the $13^{\text{th}}$ month. The total volume of loan supply of better-capitalized banks banks in the thirteenth month declined by 90.4% compared to the pre-regulation month. The pre-regulation coefficient estimates for total loans (Figure 3.12) also indicate that none are different from zero suggesting the validity of the

Figure 3.13: Sensitivity analysis for ATE on ln(Total loan) over 10 months

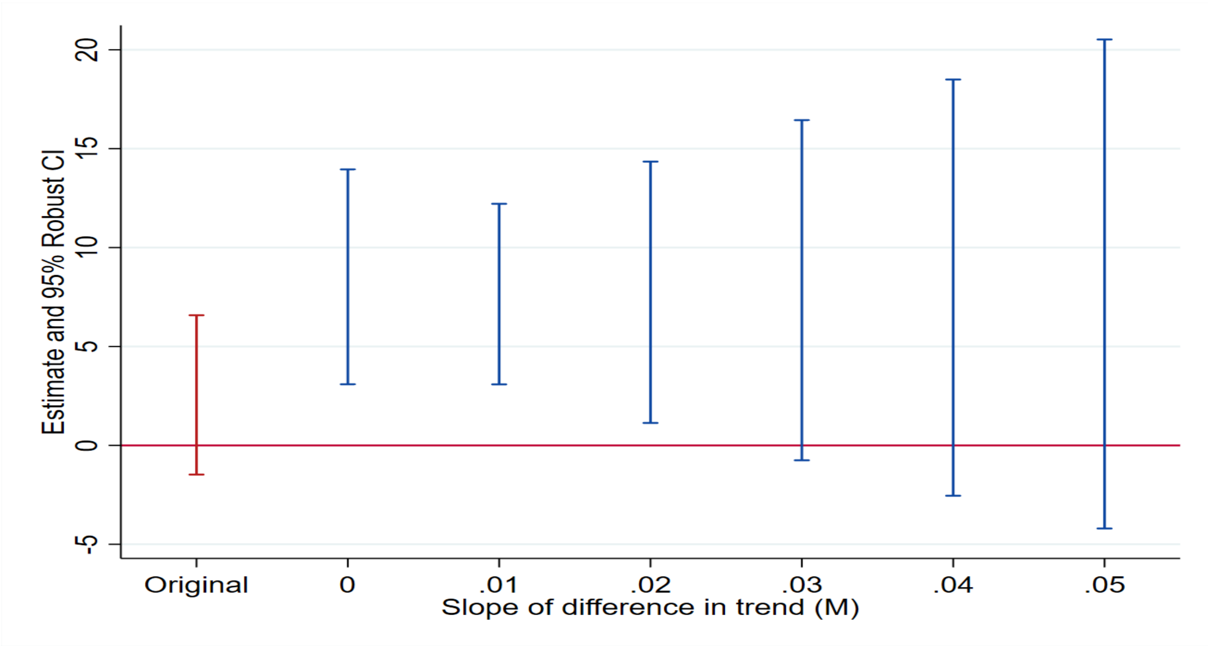
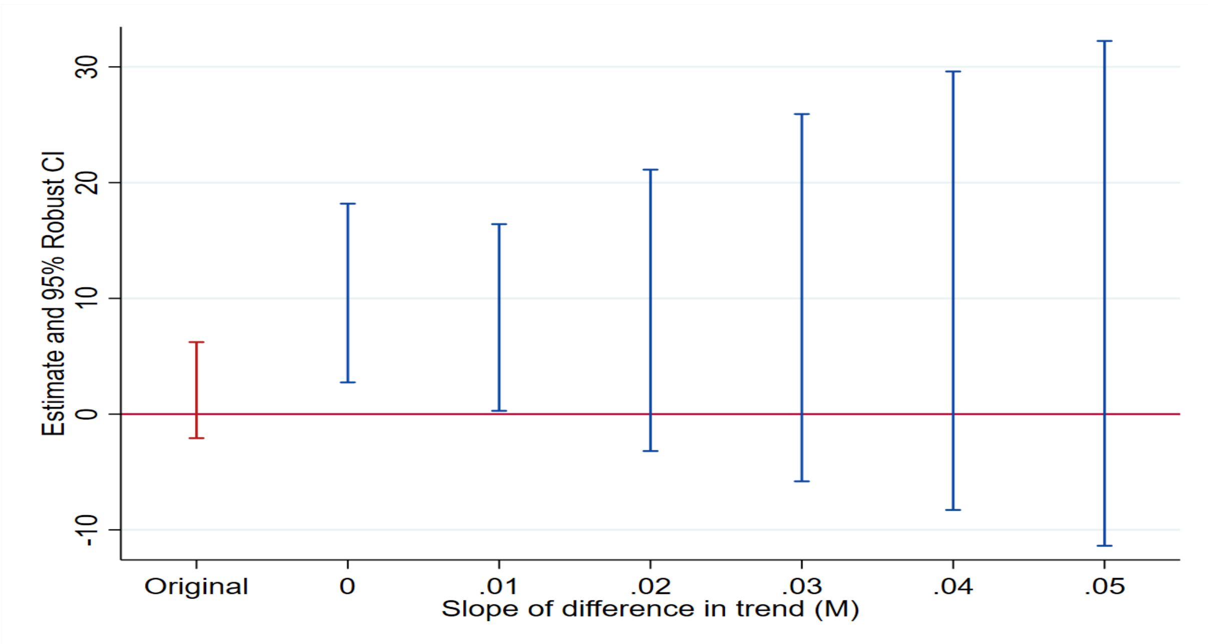



Figure 3.14: Sensitivity analysis of ATE on ln(Total Loan) over 13 months




identification strategy. However, I undertook a sensitivity analysis for the ATE of the regulation on the total volume of loan supply over 13 months after the policy change). The results (Figure 3.14) show that after allowing for a violation of parallel trends that are approximately linear (M=0), the robust confidence interval excludes zero. The 'breakdown" value of no null effect is around M=0.02 where the robust confidence interval marginally excludes zero. The absence of a negative effect of the regulation of total loan supply could partly be related to the introduction of the new regulation by the NBE which reversed the liquidity drainage experienced by banks in the short run by reducing the mandatory reserve requirement and liquidity ratio in January 2012. The implementation of the new regulation coincides with the time when the regulation is expected to have a negative impact.

### II. Average loan

Banks may respond to the policy change by adjusting the size of the loan they originate. This section explores the effect of the regulation on the average loan disbursed to each firm-cluster: industry-region. Columns (3) and (4) of Table 3.3 present the effect of the regulation on the average loan both in the short and long event windows. The result for the short event window presented in column (3) indicates that in the second month, the average loan granted by better-capitalized banks banks declined by about 242.1%, which is significant at a 1% significant level. Though the effect of the regulation is negative in other post-regulation months, none of these effects are significant at a conventional significance level except in the third month when it declined by 152%, which is significant at a 10% significance level. The result in column (4) for the long run shows that though all the post-regulation coefficients are negative, none are significant suggesting that the policy change did not affect average loans in any of the post-regulation months except for the second and third months.

The pre-treatment event study coefficient estimates for the average loan (Figure 3.15, however, indicates a violation of the pre-trend assumption in moving from the ninth lead to the eighth lead at a 5% significance level.[9] The sensitivity analysis for the ATE over 10 months (Figure 3.16) and 13 months Figure 3.17 after imposing a linear smoothness restriction indicates that the regulation has a negative and significant negative effect on average loans both in the short and long event windows with the "breakdown value" of M=0.01. The preceding analysis confirms that though better-capitalized banks increased their total volume of loans in the post-regulation period, they responded to the regulation

[9]The pre-trend test for the short run also provides the same result(Figure C.8).

Figure 3.15: Event study coefficient estimates for ln(Average loan)

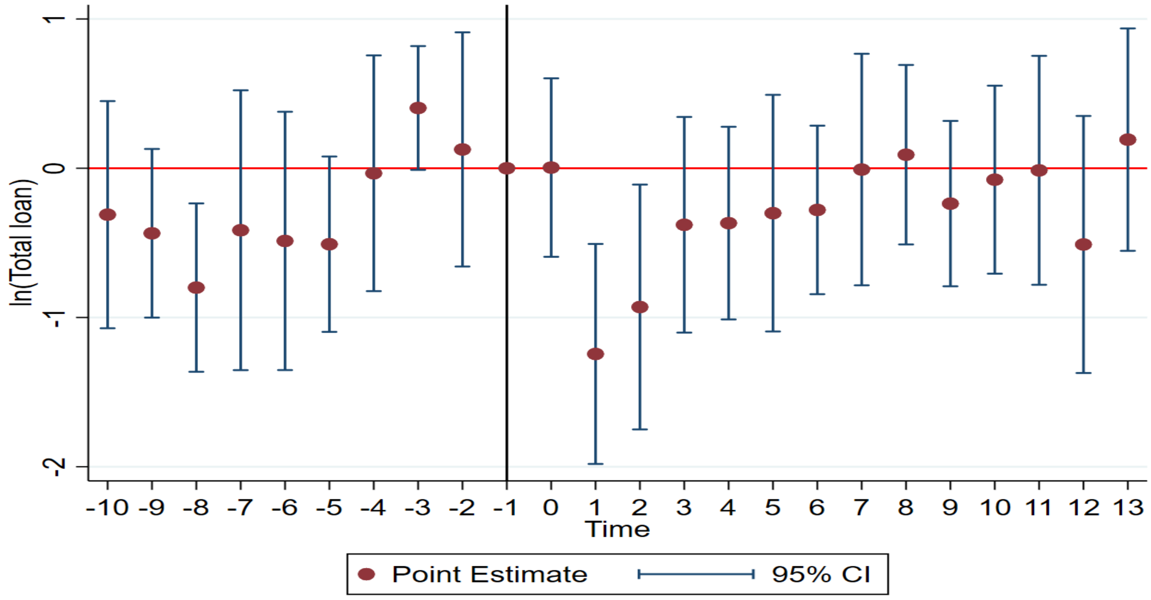
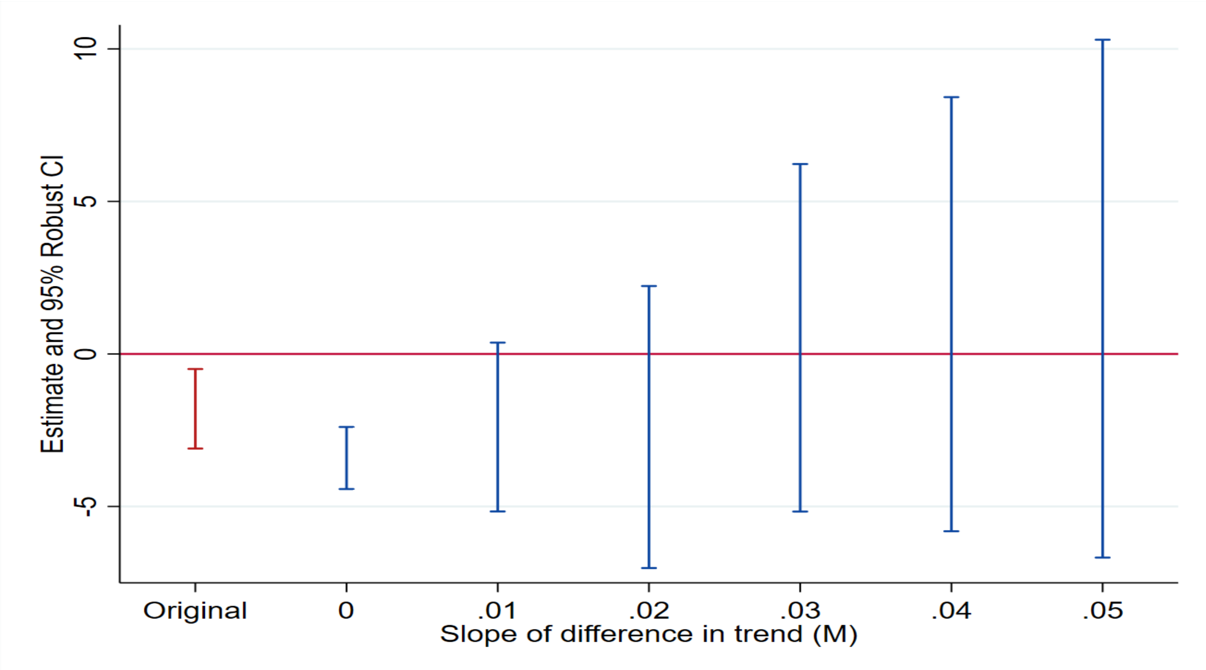


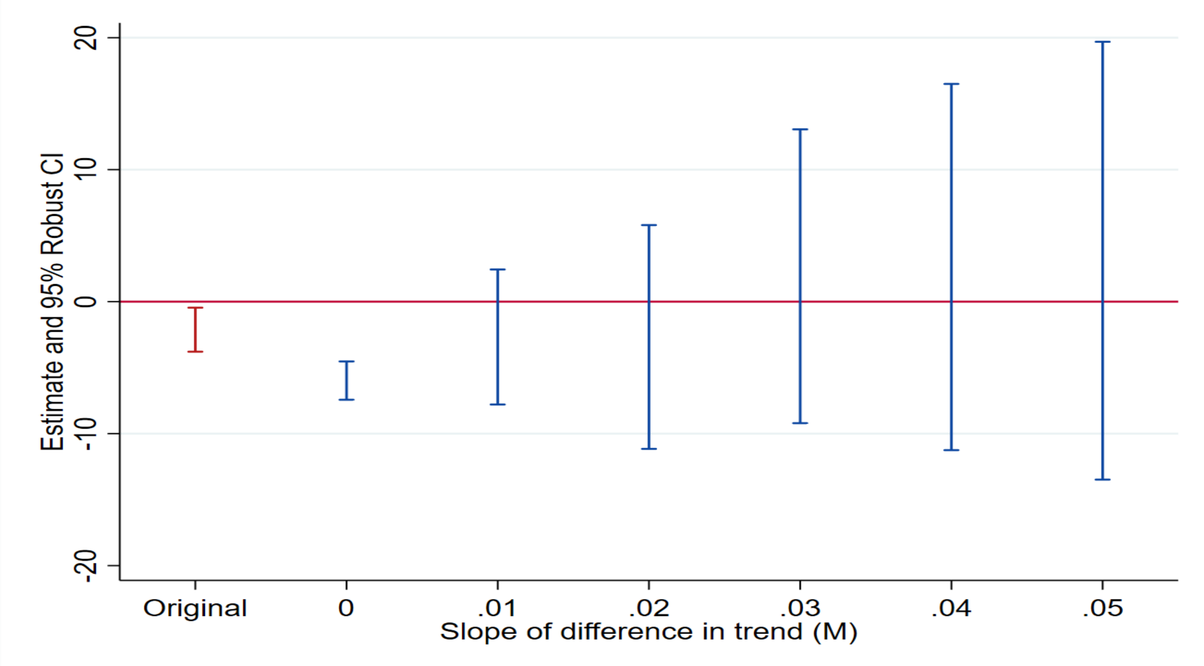

Figure 3.16: Sensitivity analysis for ATE on ln(Average loan) over 10 months




by reducing the average loan size.

Considering the regulation as an instrument for government borrowing (IMF 2013, 2018, Limodio & Strobbe 2016), the increase in the total volume of loans to the private sector could be considered as consistent with the risk diversification theory that government borrowing might induce banks to undertake relatively more risky private lending

Figure 3.17: Sensitivity analysis for ATE on ln(Average loan) over 13 months




(Kumhof & Tanner 2005). The contemporary decline in the average size of loans and the mandatory purchase of the NBE bills, however, casts doubt on this interpretation. So, the observed increase in the volume of loans by better-capitalized banks therefore could be related simply to the availability of loanable funds in the short run (Kashyap & Stein 1994). In addition, the decline in the average loan also confirms that the risk diversification theory did not hold in Ethiopia during the study period.

## B. Extensive margin of lending

One of the major functions of banks is the transformation of liquid liabilities (e.g. deposits) into illiquid assets (e.g. long-term loans), which creates a liquidity mismatch that may give rise to risk (Diamond & Dybvig 1983). To reduce this liquidity risk, liquidity-constrained banks in general are more likely to originate short-term loans or loans with short repayment periods (higher frequency of repayment). The liquidity drainage induced by the regulation creates additional liquidity risk which changes banks' lending behavior in the extensive margin of lending. Moreover, since banks reduce the average size of the loan the observed rise in the total volume of loan supply could be related to another extensive margin of lending, the number of approved(outstanding) loans. This section examines the impact of the regulation on the extensive margin of lending using a loan repayment period and the number of outstanding loans. Table 3.4 presents the event study coefficients estimates for the ln(Repayment period) and the ln(Number of loans) based on equation(1).[10] All models include bank, month, cluster, and cluster X-month fixed effects, and the standard errors are clustered at bank and cluster levels.

## I. Loan repayment period

The impact of the regulation on the loan repayment period in the short event window is presented in column (1). The result indicates that the regulation had a significant negative effect in most of the post-regulation months. In the second month, the policy reduced the loan repayment period of better-capitalized banks by around 15.8% relative to the pre-regulation month. This effect rises to 28.5% in the sixth month. These effects are significant at a 10% significance level. The long-run effect presented in column (2) shows that the negative effect persists. In the 11$^{th}$ month, better-capitalized banks reduced the loan repayment period by around 25.5%, which is significant at a 5% significance level and suggests that banks increase loan repayment frequency to mitigate the liquidity drainage both in the short and long event windows.

Looking at the pre-regulation coefficient estimates for loan repayment in the long event window (Figure 3.18) shows that the coefficient estimate for the ninth lead is statistically different from zero at a 5% significance level suggesting the pre-trend assumption does not hold for the loan repayment period. The pre-test for the loan repayment period in the short event window shows the same result (see, Figure C.9). The sensitivity analysis for the ATE on loan repayment over 10 months allowing for a linear violation of the parallel trend indicates the effect is negative and significant with a "breakdown value" of M=0.02 (Figure 3.19). The result is the same for ATE over 13 months with the "breakdown value" of M=0.01 (Figure 3.20).

[10] The coefficient estimates and the bootstrap clustered standard errors from OLS regression for the ln(Repayment period) (Table C.4) and the ln(Number of loans) (Table C.5) when standard errors are clustered at the bank level are similar to the HDFE estimates.

Table 3.4: Impact on loans repayment period and number of outstanding loans

| | ln(Repayment period) | | ln(Number of loans) | |
|---|---|---|---|---|
| | (1) Short-term | (2) Long-term | (3) Short-term | (4) Long-term |
| 1st Month | -0.002 | -0.006 | 0.493 | 0.500 |
| | (0.074) | (0.075) | (0.312) | (0.310) |
| 2nd Month | -0.149* | -0.149* | 0.354 | 0.357 |
| | (0.080) | (0.080) | (0.348) | (0.350) |
| 4th Month | -0.165 | -0.164 | 0.685* | 0.694* |
| | (0.148) | (0.147) | (0.331) | (0.336) |
| 5th Month | -0.193 | -0.191 | 0.456 | 0.464 |
| | (0.141) | (0.142) | (0.290) | (0.295) |
| 6th Month | -0.256* | -0.251* | 0.639* | 0.656* |
| | (0.124) | (0.124) | (0.352) | (0.356) |
| 7th Month | -0.174 | -0.173 | 0.511 | 0.522 |
| | (0.126) | (0.125) | (0.350) | (0.355) |
| 8th Month | -0.004 | -0.005 | 0.382 | 0.379 |
| | (0.130) | (0.130) | (0.345) | (0.346) |
| 9th Month | -0.153 | -0.152 | 0.068 | 0.062 |
| | (0.099) | (0.098) | (0.441) | (0.442) |
| 10th Month | -0.186 | -0.186 | 0.144 | 0.149 |
| | (0.125) | (0.124) | (0.394) | (0.397) |
| 11th Month | - | -0.228** | - | -0.044 |
| | | (0.098) | | (0.405) |
| 12th Month | - | -0.196 | - | -0.096 |
| | | (0.135) | | (0.409) |
| 13th Month | - | -0.138 | - | -0.320 |
| | | (0.128) | | (0.356) |
| $N$ | 2295 | 2617 | 2295 | 2617 |
| adj. $R^2$ | 0.296 | 0.292 | 0.497 | 0.484 |
| Bank FEs | Yes | Yes | Yes | Yes |
| Month FEs | Yes | Yes | Yes | Yes |
| Cluster FEs | Yes | Yes | Yes | Yes |
| Cluster-Month FEs | Yes | Yes | Yes | Yes |

N.B.: The table shows the post-regulation monthly estimates from the event study model of equation(1). The dependent variable in columns(1) and column(2) is ln(Repayment period) and it is ln(Number of loans) in columns(3) and column(4). The estimate in Column (1) and Column (3) is for short event wind while Column (2) and Column (4) show the result for longer event windows where the post-regulation period is extended to 13 months. The standard errors clustered at the bank level are in parentheses. *p $<$ 0.10, **p $<$ 0.05,***p $<$ 0.01.

## II. Outstanding number of loans

The impact of the regulation on the number of outstanding loans is presented in column (3) and column (4) of Table 3.4. The result for the short event window indicates that the effect of the policy change for all of the post-treatment months is positive. In the

Figure 3.18: Event study coefficient estimates for ln(Repayment period) over 13 months

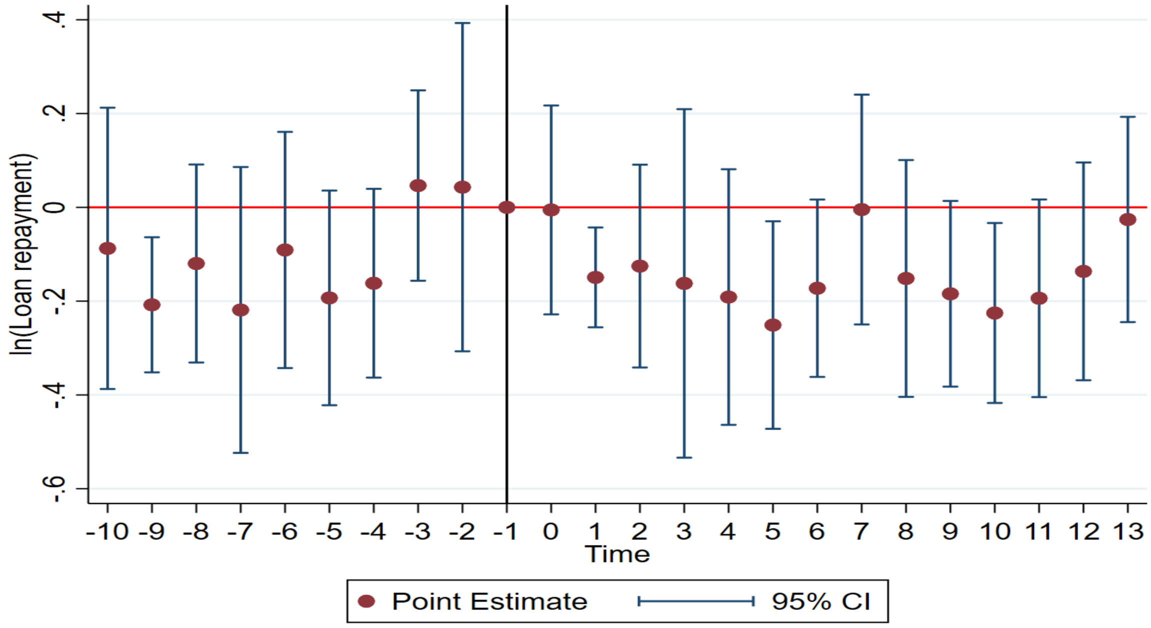
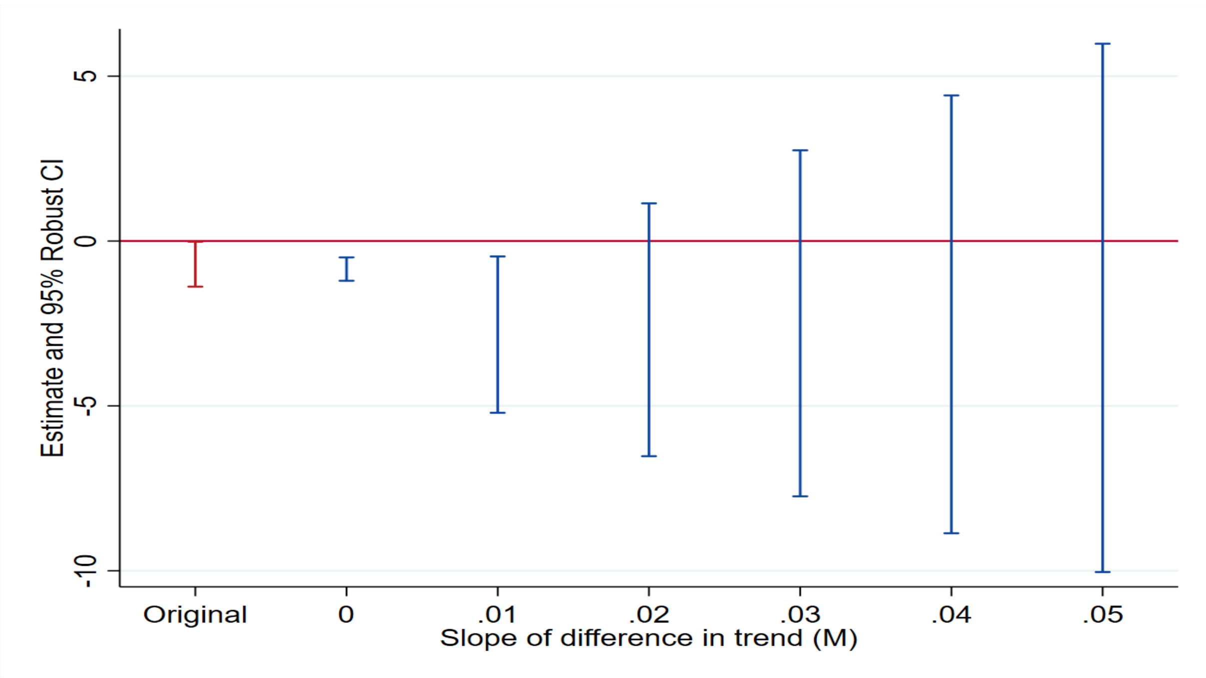
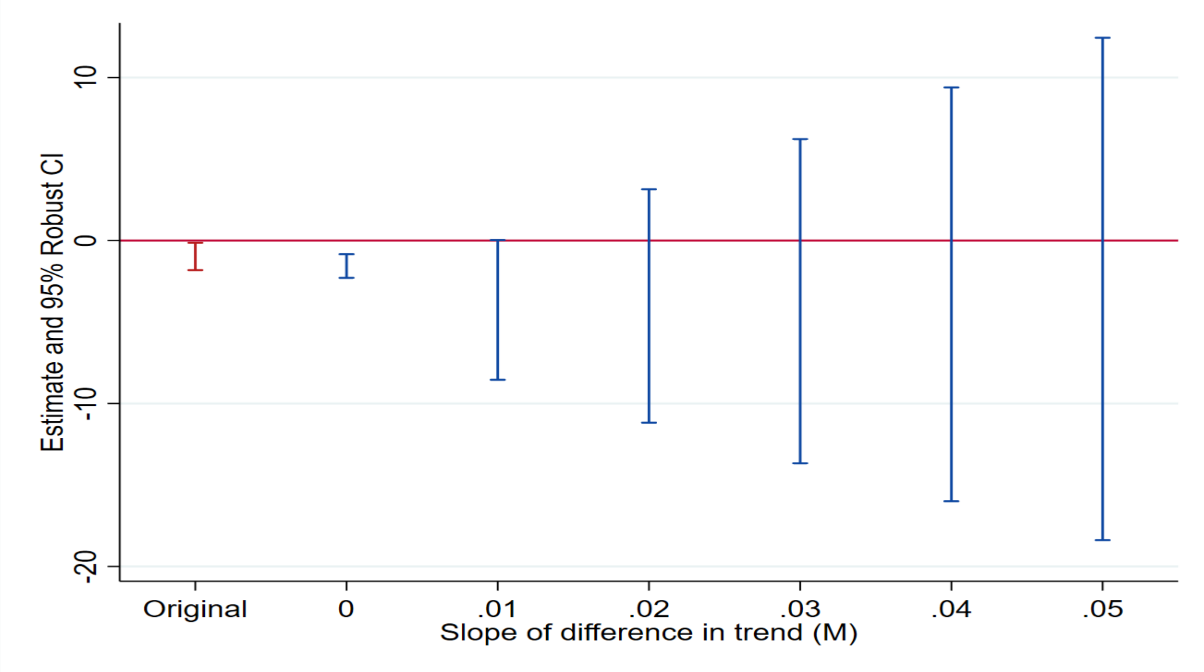



Figure 3.19: Sensitivity analysis for ATE on ln(Repayment period) over 13 months




4th and 6th months, the number of outstanding loans increased by about 98% and 90% respectively. For the long-run period presented in Column (4) the result shows that the positive effects of the regulation in the fourth and sixth months are the same. These estimates are significant at a 10% significant level. The effects of the regulation turned out to be negative in the ninth month and continued to be negative thereafter. However,

Figure 3.20: Sensitivity analysis for ATE on ln(Repayment period) over 13 months




none of the estimates are significant, suggesting that the regulation did not affect the number of outstanding loans in any post-regulation period.

The event study coefficient estimates for the number of outstanding loans presented in Figure 3.21 show that all pre-regulation coefficient estimates are not statistically different from zero and suggest the violation of pre-trend. The result is the same for the short event window (see, Figure C.10). The sensitivity analysis imposes similar linear smoothness restrictions as before and indicates (Figure 3.22) that the robust 95% confidence interval excludes zero and provides evidence for the positive effect of the regulation on the outstanding number of loans at a 5% significance level in the short event window with a "breakdown value" of around M=0.1. The ATE over 13 months (Figure 3.23) also clearly shows that the regulation had a positive impact on the number of outstanding loans.

The preceding analysis confirms that more-capitalized banks that experience a liquidity shock transmit this shock to borrower by reducing the average loan and loan repayment period, and confirms the existence of a bank lending channel in an economy where standard monetary policy instruments targeting interest rates are absent. At the same time, these banks increased the total loan supply and the number of loans as measured by the

Figure 3.21: Event study coefficient estimates for ln(Number of loans)

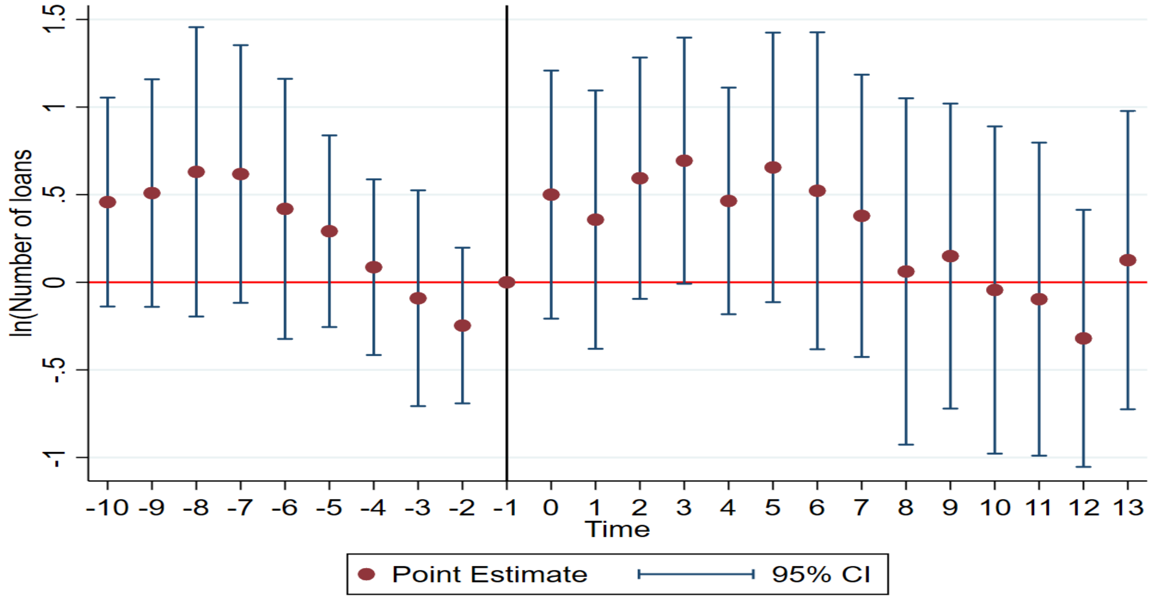
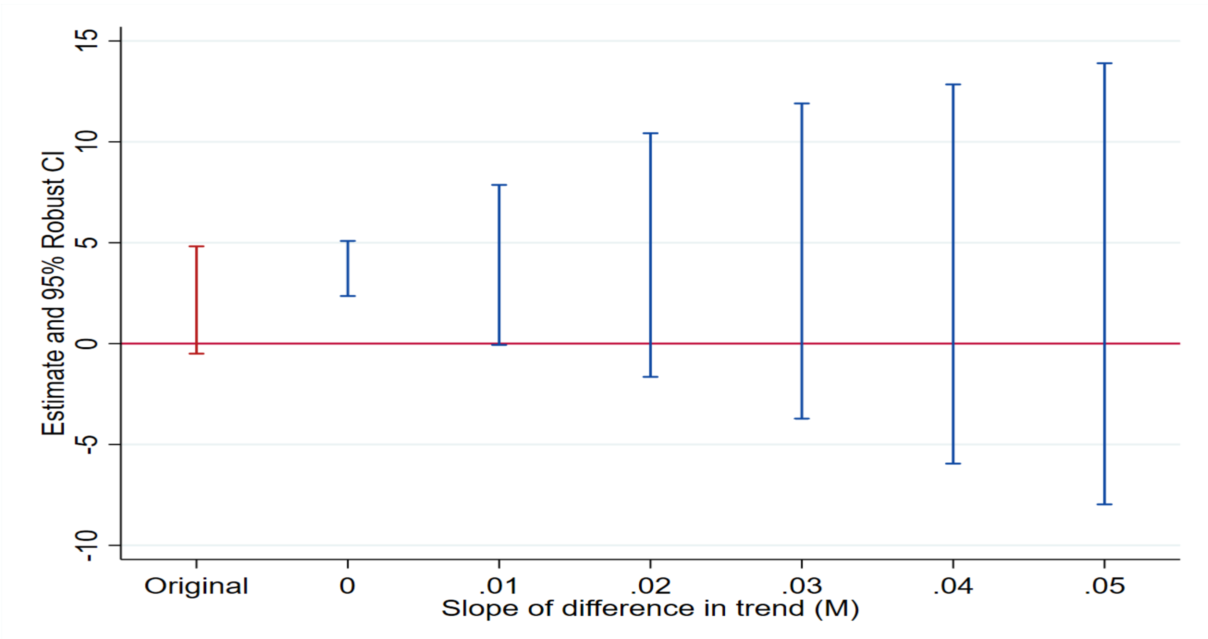
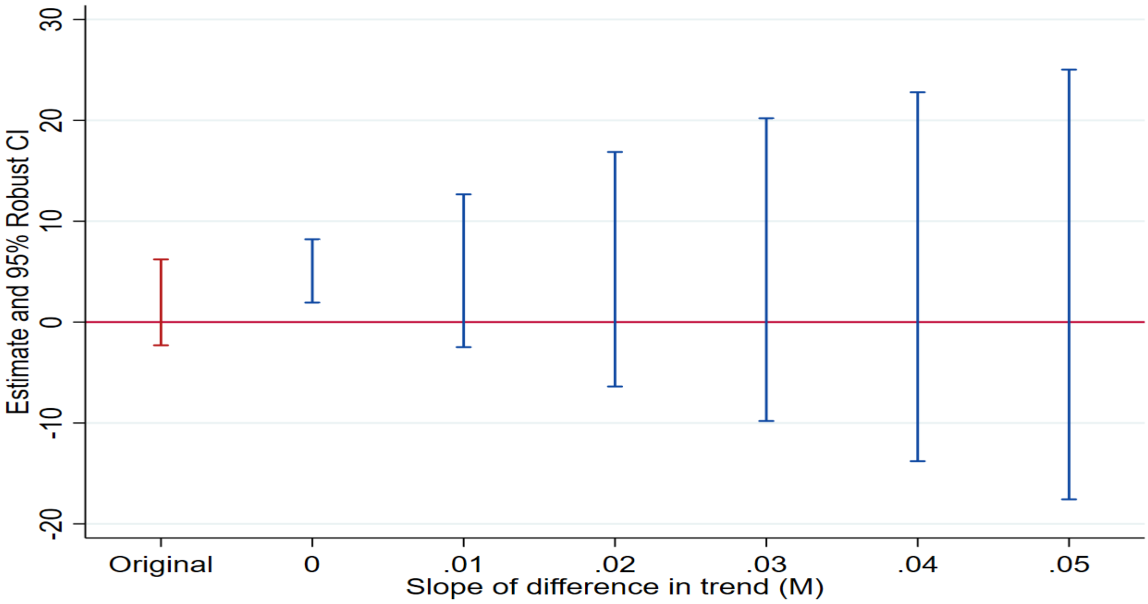



Figure 3.22: Sensitivity analysis for ln(Number of loans) over the period of 10 months




total number of outstanding loans. This suggests that the policy change caused treated banks to engage in credit rationing by providing small-size loans with high repayment frequency to a large number of borrowers thereby increasing the total volume of loan supply both in the short and long event windows. The absence of a negative effect on the total volume of loan supply could be related to the new regulatory policy changes that were implemented at the time when the regulation was expected to have a negative

Figure 3.23: Sensitivity analysis for ATE on the ln(Number of loans) over the period of 13 months




impact because of its lag effect, These policy changes reduced the reserve requirement and liquidity ratio in January 2012 and reversed bank liquidity drainage induced by the NBE-bill regulation as indicated in Figure 3.2.

## 3.6 Conclusion

Many developing countries have adopted standard monetary policy instruments targeting interest rates to affect credit supply and economic activities. Some developing countries are, however, still characterized by underdeveloped interbank markets and concentrated banking systems with excess liquidity which is believed to have limited the working of bank lending channel. It is unclear whether banks in these countries transmit liquidity shock and bank lending channel works. This paper explores the impact of liquidity shock on bank lending behavior in an economy where banks are the dominant financial institutions and standard monetary policy is absent. Examining the causal impact of a liquidity shock on bank lending behavior, however, entails significant identification challenges for two reasons. First, a liquidity shock is mainly systemic affecting all banks simultaneously, and requires identification of how a universal liquidity shock exposes banks to differential liquidity shocks. Second, loan supply is endogenous to bank lending policies, and banks experiencing a liquidity shock might face a simultaneous decline in firms' credit demand. Quantifying bank lending channels resulting from liquidity shock thus requires separating the credit supply from credit demand using high-quality microdata that can capture credit demand.

To obtain exogenous variation in bank exposure to a liquidity shock, this study uses the mandatory regulatory policy change on new bill purchases by the National Bank of Ethiopia (NBE) as a natural experiment. The regulation was applied indiscriminately across all banks. The sudden announcement and immediate application of the regulation in April 2011, however, exposed banks to a differential liquidity shock based on their balance sheet strength. The study thus exploits the pre-regulation cross-sectional bank's balance sheet strength measured by capital and assigned banks into two cohorts that vary in their exposure to the liquidity shock: more capitalized banks and less-capitalized ones. If the regulatory policy affects banks' loan supply, this effect has to come through liquidity drainage. The study hypothesizes that more capitalized banks with more capital were more liquid and lent more before the regulation and will continue lending more even after the regulation. Since the regulation requires all banks to allocate 27% of the new gross loan disbursement for the purchase of NBE bills, this will eventually lead to liquidity drainage and translate into a decline in credit supply by this group of banks compared to under-capitalized banks (the control group).

The study uses two sets of confidential data from the NBE and employs an even study design to estimate the causal impact of the regulation on credit supply. The first is banks' balance sheet information to understand the transmission mechanism of the bank lending channel. The second data source is the credit register loan-level microdata. Due to the prevalence of a single bank relationship, the data are clustered in a firm-cluster: industry and region. All variables are expressed in a natural logarithm. In addition to bank and month fixed effects, the event study design model includes firm-cluster X month fixed effect to control for credit demand shocks that vary by cluster and month.

The result from the HDFE estimation method shows that large banks transmit the liquidity shock induced by the regulation more compared to under-capitalized banks confirming the presence of a bank lending channel of a liquidity shock. The result, after allowing the violation of the parallel trend and imposing smoothness restrictions, indicates that the regulations caused large banks to tighten the average loan volume and loan repayment period, but to increase the total volume of loans and the number of outstanding loans in the short event window. The study thus concludes that the regulation caused banks to engage in credit rationing by providing more small-sized loans with higher repayment frequency while increasing the total volume of loan supply both in the short and long event windows.

The study contributes to the literature related to the bank lending channel of liquidity shock/monetary policy. The main caveat of the study is that it simply focuses on the transmission of the liquidity shock and examines the existence of the bank lending channel in relatively short and long event windows. The research could be extended to looking at the impact of the regulation on other dimensions such as inflation, branch expansion as in Limodio & Strobbe (2023), deposit mobilization and firm performance to give valuable insight to understand the overall effect of the policy change.

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# Appendix C

# Tables and Figures

Figure C.1: Liquidity and loan of larger and smaller banks before and after the regulation.

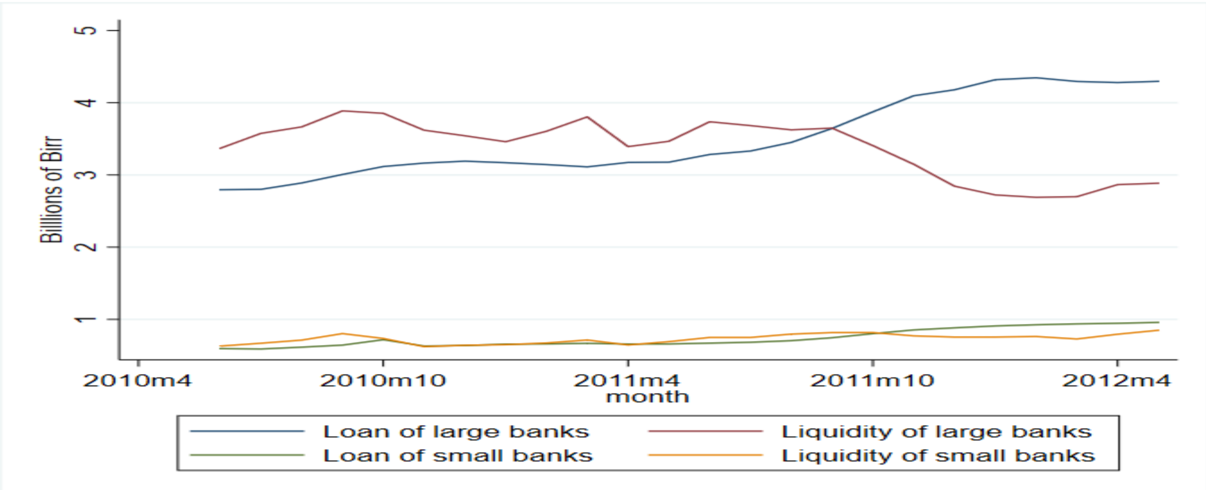


Figure C.2: Pre-regulation coefficient estimates for ln(Liability)

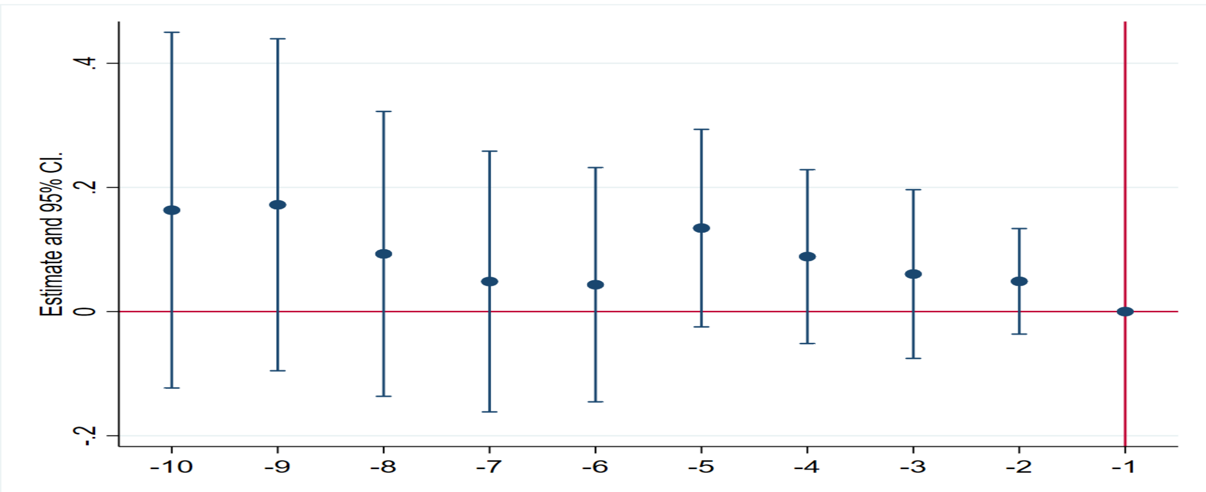

Figure C.3: Event study coefficient estimates for ln(Capital)

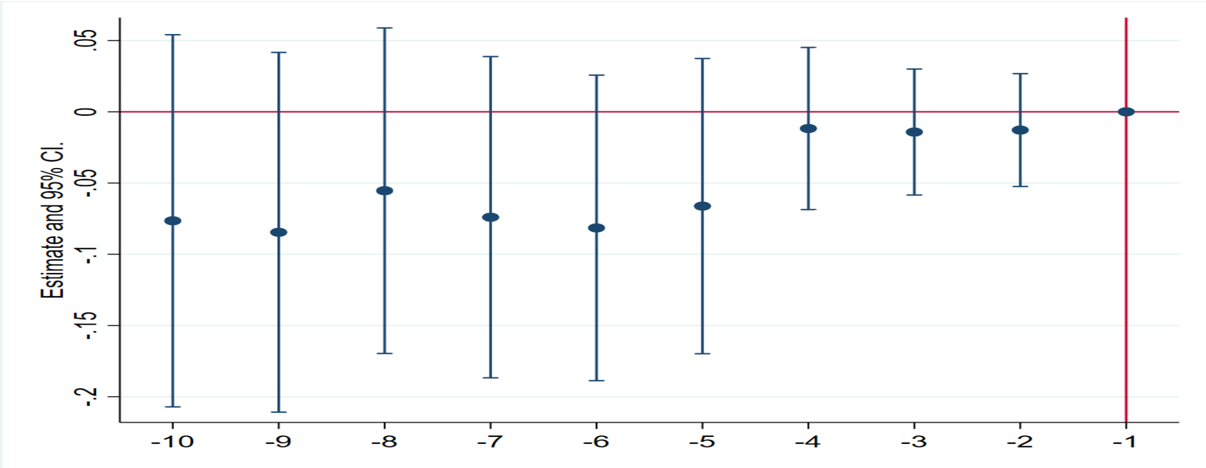


Figure C.4: Event study coefficient estimates for $\beta_{10}$ for ln(Deposit with banks).

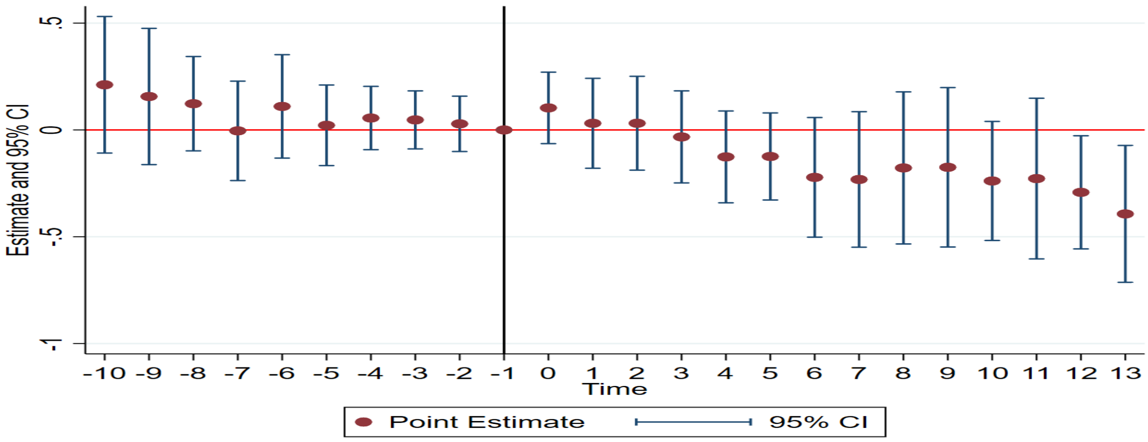


Figure C.5: Sensitivity analysis for ATE on ln(Liquid asset) for $\beta_{10}$.

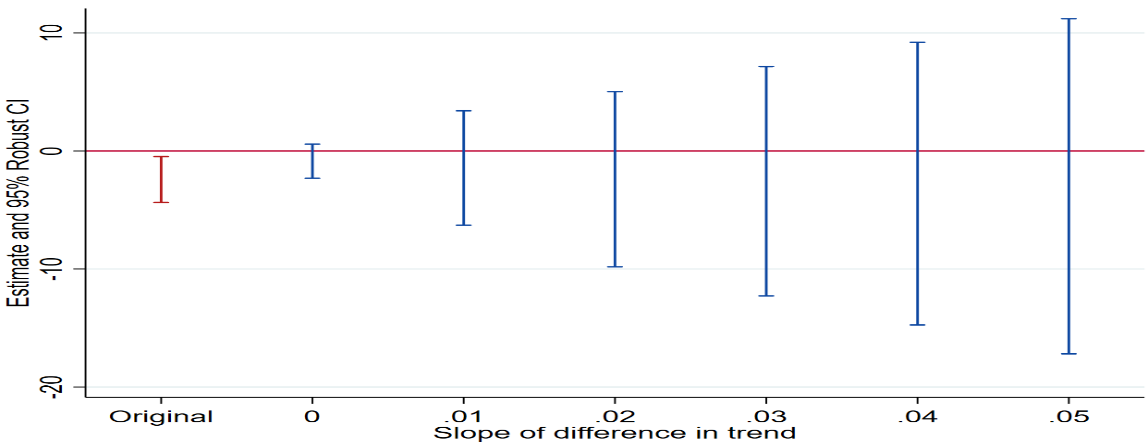

Figure C.6: Sensitivity analysis for ATE on ln(Liquid asset) for a period of 10 months.

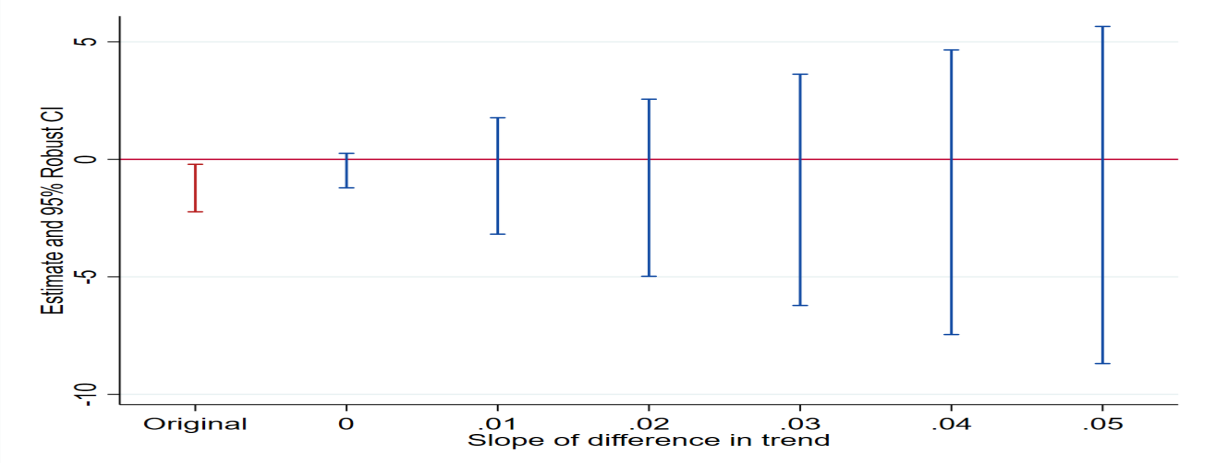


Figure C.7: Event study coefficient estimates for ln(Total loan) in the short run

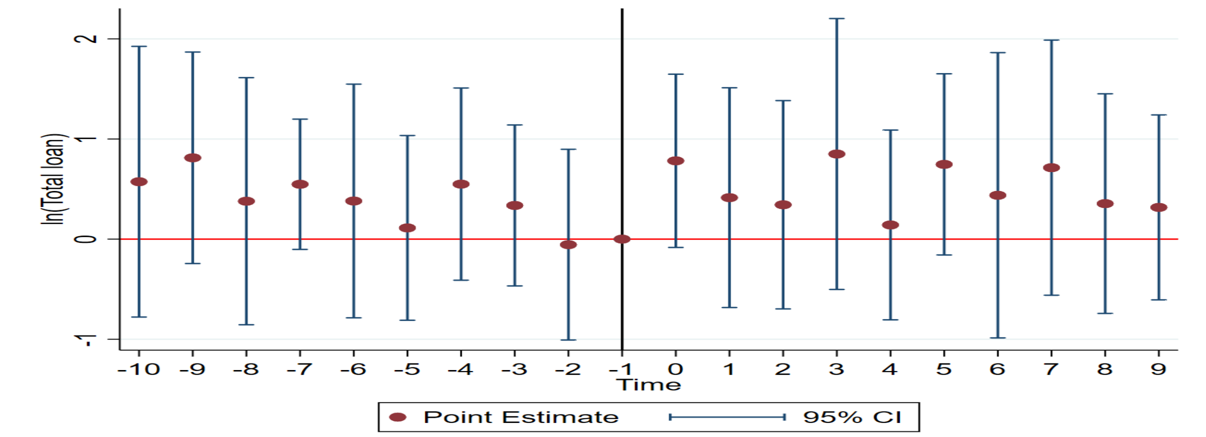


Figure C.8: Event study coefficient estimates for ln(Average loan) in the short run

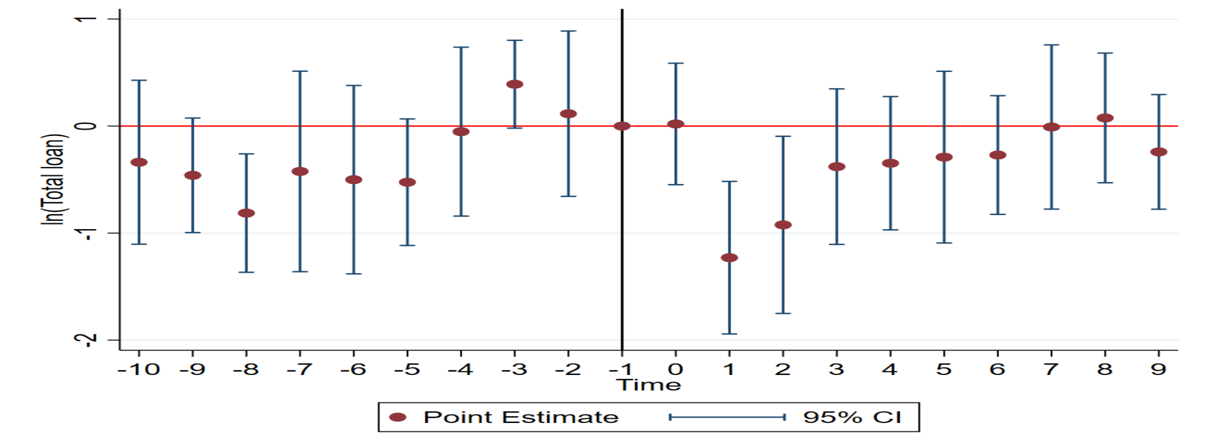

Figure C.9: Event study coefficient estimates for ln(Repayment period) in the short run

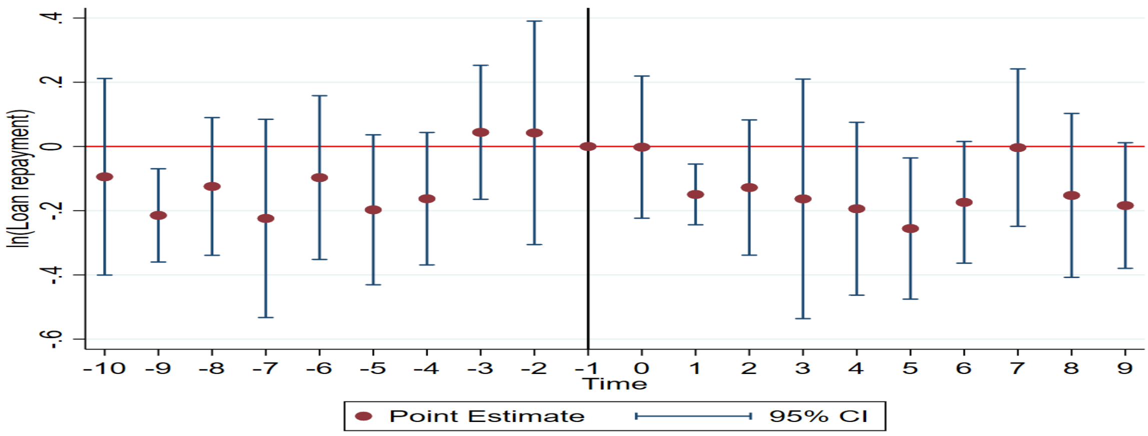


Figure C.10: Event study coefficient estimates for ln(Number of loans) in the short event window

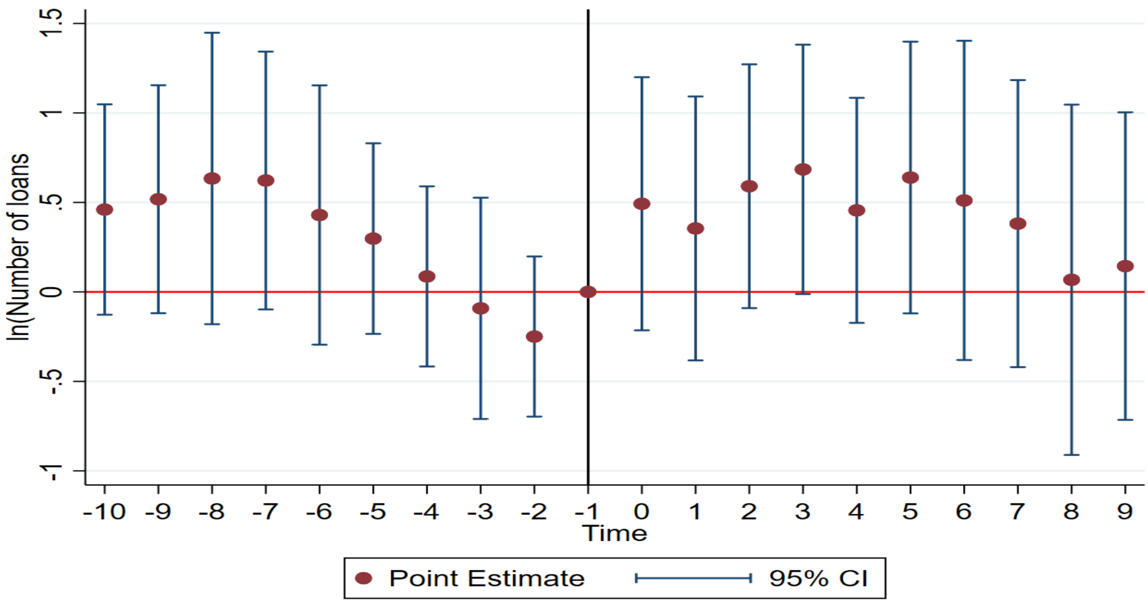

Table C.1: The impact of the regulation on liquidity and its components using OLS and HDFE methods.

| | Liquid asset | | Cash on hand | | Bank depost | |
|---|---|---|---|---|---|---|
| | (1) OLS | (2) HDFE | (3) OLS | (4) HDFE | (5) OLS | (6) HDFE |
| 1st Month | -0.027 | -0.027 | -0.298** | -0.298** | 0.103 | 0.103 |
| | (0.069) | (0.067) | (0.114) | (0.111) | (0.079) | (0.077) |
| 2nd Month | -0.117 | -0.117 | -0.403** | -0.403** | 0.031 | 0.031 |
| | (0.090) | (0.088) | (0.161) | (0.158) | (0.100) | (0.097) |
| 3rd Month | -0.130 | -0.130 | -0.482** | -0.482** | 0.031 | 0.031 |
| | (0.102) | (0.100) | (0.177) | (0.173) | (0.104) | (0.102) |
| 4th Month | -0.168 | -0.168 | -0.472*** | -0.472*** | -0.033 | -0.033 |
| | (0.107) | (0.105) | (0.156) | (0.153) | (0.102) | (0.100) |
| 5th Month | -0.243** | -0.243** | -0.516** | -0.516** | -0.126 | -0.126 |
| | (0.109) | (0.107) | (0.176) | (0.172) | (0.102) | (0.099) |
| 6th Month | -0.232** | -0.232** | -0.478** | -0.478** | -0.124 | -0.124 |
| | (0.098) | (0.096) | (0.187) | (0.182) | (0.097) | (0.094) |
| 7th Month | -0.309** | -0.309** | -0.662** | -0.662*** | -0.222 | -0.222 |
| | (0.130) | (0.127) | (0.224) | (0.219) | (0.133) | (0.130) |
| 8th Month | -0.369* | -0.369* | -0.704** | -0.704** | -0.232 | -0.232 |
| | (0.178) | (0.173) | (0.294) | (0.287) | (0.150) | (0.147) |
| 9th Month | -0.418** | -0.418** | -0.692** | -0.692** | -0.178 | -0.178 |
| | (0.170) | (0.166) | (0.287) | (0.280) | (0.169) | (0.165) |
| 10th Month | -0.429** | -0.429** | -0.825*** | -0.825*** | -0.175 | -0.175 |
| | (0.173) | (0.169) | (0.264) | (0.258) | (0.177) | (0.173) |
| $N$ | 331 | 331 | 331 | 331 | 331 | 331 |
| adj. $R^2$ | 0.975 | 0.975 | 0.903 | 0.903 | 0.972 | 0.972 |

Note: The table shows the post-regulation monthly estimates from the event study model of equation(1) for liquid asset and its components. All regressions include bank and month-fixed effects. The (bootstrapped) standard errors in parentheses (for the OLS regression) are clustered at the bank level. *p $<$ 0.10, **p $<$ 0.05,***p $<$ 0.01

Table C.2: OLS and HDFE estimates for the impact of the regulation on ln(Total loan)

| | Short-term | | Long-term | |
|---|---|---|---|---|
| | (1)<br>OLS | (2)<br>HDFE | (3)<br>OLS | (4)<br>HDFE |
| 1st Month | 0.782** | 0.782** | 0.778** | 0.778** |
| | (0.344) | (0.329) | (0.343) | (0.327) |
| 2nd Month | 0.414 | 0.414 | 0.404 | 0.404 |
| | (0.568) | (0.542) | (0.570) | (0.543) |
| 4th Month | 0.850 | 0.850* | 0.870 | 0.870* |
| | (0.492) | (0.469) | (0.500) | (0.477) |
| 6th Month | 0.746 | 0.746 | 0.767 | 0.767 |
| | (0.467) | (0.446) | (0.472) | (0.450) |
| 7th Month | 0.438 | 0.438 | 0.446 | 0.446 |
| | (0.556) | (0.531) | (0.564) | (0.537) |
| 8th Month | 0.714 | 0.714 | 0.712 | 0.712 |
| | (0.527) | (0.503) | (0.527) | (0.502) |
| 9th Month | 0.355 | 0.355 | 0.362 | 0.362 |
| | (0.525) | (0.501) | (0.524) | (0.500) |
| 10th Month | 0.317 | 0.317 | 0.342 | 0.342 |
| | (0.449) | (0.429) | (0.446) | (0.425) |
| 11th Month | - | - | -0.081 | -0.081 |
| | | | (0.530) | (0.505) |
| 12th Month | - | - | -0.290 | -0.290 |
| | | | (0.476) | (0.453) |
| 13h Month | - | - | -0.645 | -0.645* |
| | | | (0.369) | (0.351) |
| $N$ | 2502 | 2295 | 2867 | 2617 |
| adj. $R^2$ | 0.545 | 0.525 | 0.532 | 0.513 |
| Bank FEs | Yes | Yes | Yes | Yes |
| Month FEs | Yes | Yes | Yes | Yes |
| Cluster FEs | Yes | Yes | Yes | Yes |
| Cluster-Month FEs | Yes | Yes | Yes | Yes |

N.B.: The table shows the post-regulation monthly estimates from the event study model of equation(1). The dependent variable is ln(Total loan). The estimate in column(1) and column (2) is for short event windows while Column (2) and Column (4) present the result for longer event windows, The standard errors clustered at the bank level are in parentheses. *p $<$ 0.10, **p $<$ 0.05,***p $<$ 0.01

Table C.3: OLS and HDFE estimates for the impact of the regulation on ln(Average loan)

| | Short-term | | Long-term | |
|---|---|---|---|---|
| | (1) OLS | (2) HDFE | (3) OLS | (4) HDFE |
| 1st Month | 0.014 | 0.014 | -0.000 | -0.000 |
| | (0.329) | (0.314) | (0.328) | (0.312) |
| 2nd Month | -1.236** | -1.236*** | -1.250** | -1.250*** |
| | (0.421) | (0.401) | (0.423) | (0.402) |
| 4th Month | -0.375 | -0.375 | -0.375 | -0.375 |
| | (0.333) | (0.318) | (0.335) | (0.318) |
| 6th Month | -0.285 | -0.285 | -0.296 | -0.296 |
| | (0.440) | (0.419) | (0.443) | (0.421) |
| 7th Month | -0.267 | -0.267 | -0.276 | -0.276 |
| | (0.422) | (0.403) | (0.423) | (0.402) |
| 8th Month | -0.010 | -0.010 | -0.010 | -0.010 |
| | (0.446) | (0.425) | (0.449) | (0.428) |
| 9th Month | 0.081 | 0.081 | 0.094 | 0.094 |
| | (0.277) | (0.264) | (0.276) | (0.263) |
| 10th Month | -0.241 | -0.241 | -0.237 | -0.237 |
| | (0.253) | (0.241) | (0.250) | (0.237) |
| 11th Month | - | - | -0.073 | -0.073 |
| | | | (0.288) | (0.274) |
| 12th Month | - | - | -0.007 | -0.007 |
| | | | (0.380) | (0.362) |
| 13h Month | - | - | -0.501 | -0.501 |
| | | | (0.451) | (0.429) |
| $N$ | 2596 | 2375 | 2961 | 2697 |
| Adj. $R^2$ | 0.332 | 0.305 | 0.328 | 0.302 |
| Bank FEs | Yes | Yes | Yes | Yes |
| Month FEs | Yes | Yes | Yes | Yes |
| Cluster FEs | Yes | Yes | Yes | Yes |
| Cluster-Month FEs | Yes | Yes | Yes | Yes |

N.B.: The table shows the post-regulation monthly estimates from the event study model of equation(1). The dependent variable is ln(Average loan). The estimate in column(1) and column (2) is for short event windows while Column (2) and Column (4) present the result for longer event windows, The standard errors clustered at the bank level are in parentheses. *p $<$ 0.10, **p $<$ 0.05,***p $<$ 0.01.

Table C.4: OLS and HDFE estimates for the impact of the regulation on lm(Repayment period)

| | Short-term | | Long-term | |
|---|---|---|---|---|
| | (1) OLS | (2) HDFE | (3) OLS | (4) HDFE |
| 1st Month | -0.001 | -0.001 | -0.005 | -0.005 |
| | (0.078) | (0.074) | (0.079) | (0.075) |
| 2nd Month | -0.147 | -0.147* | -0.147 | -0.147* |
| | (0.084) | (0.080) | (0.084) | (0.080) |
| 4th Month | -0.163 | -0.163 | -0.162 | -0.162 |
| | (0.155) | (0.148) | (0.155) | (0.148) |
| 6th Month | -0.255* | -0.255* | -0.251* | -0.251* |
| | (0.130) | (0.124) | (0.131) | (0.124) |
| 7th Month | -0.174 | -0.174 | -0.172 | -0.172 |
| | (0.132) | (0.126) | (0.132) | (0.125) |
| 8th Month | -0.005 | -0.005 | -0.006 | -0.006 |
| | (0.137) | (0.130) | (0.137) | (0.130) |
| 9th Month | -0.154 | -0.154 | -0.153 | -0.153 |
| | (0.104) | (0.099) | (0.104) | (0.099) |
| 10th Month | -0.185 | -0.185 | -0.185 | -0.185 |
| | (0.131) | (0.124) | (0.130) | (0.124) |
| 11th Month | - | - | -0.227** | -0.227** |
| | | | (0.103) | (0.098) |
| 12th Month | - | - | -0.195 | -0.195 |
| | | | (0.142) | (0.135) |
| 13h Month | - | - | -0.138 | -0.138 |
| | | | (0.135) | (0.129) |
| $N$ | 2596 | 2375 | 2961 | 2697 |
| adj. $R^2$ | 0.303 | 0.296 | 0.300 | 0.292 |
| Bank FEs | Yes | Yes | Yes | Yes |
| Month FEs | Yes | Yes | Yes | Yes |
| Cluster FEs | Yes | Yes | Yes | Yes |
| Cluster-Month FEs | Yes | Yes | Yes | Yes |

N.B.: The table shows the post-regulation monthly estimates from the event study model of equation(1). The dependent variable is ln(Repayment period). The estimate in column(1) and column (2) is for short event windows while Column (2) and Column (4) present the result for longer event windows, The standard errors clustered at the bank level are in parentheses. *p < 0.10, **p < 0.05,***p < 0.01

Table C.5: OLS and HDFE estimates for the impact of the regulation on ln(Number of loans)

| | Short-term | | Long-term | |
|---|---|---|---|---|
| | (1) OLS | (2) HDFE | (3) OLS | (4) HDFE |
| 1st Month | 0.491 | 0.491 | 0.499 | 0.499 |
| | (0.327) | (0.312) | (0.326) | (0.326) |
| 2nd Month | 0.355 | 0.355 | 0.358 | 0.358 |
| | (0.366) | (0.349) | (0.369) | (0.369) |
| 4th Month | 0.688* | 0.688* | 0.697* | 0.697* |
| | (0.348) | (0.332) | (0.354) | (0.354) |
| 6th Month | 0.643 | 0.643* | 0.659 | 0.659 |
| | (0.370) | (0.353) | (0.376) | (0.376) |
| 7th Month | 0.513 | 0.513 | 0.524 | 0.524 |
| | (0.369) | (0.351) | (0.374) | (0.374) |
| 8th Month | 0.383 | 0.383 | 0.380 | 0.380 |
| | (0.363) | (0.346) | (0.364) | (0.364) |
| 9th Month | 0.069 | 0.069 | 0.063 | 0.063 |
| | (0.463) | (0.441) | (0.465) | (0.465) |
| 10th Month | 0.144 | 0.144 | 0.149 | 0.149 |
| | (0.414) | (0.394) | (0.418) | (0.418) |
| 11th Month | - | - | -0.043 | -0.043 |
| | | | (0.427) | (0.427) |
| 12th Month | - | - | -0.093 | -0.093 |
| | | | (0.430) | (0.430) |
| 13h Month | - | - | -0.317 | -0.317 |
| | | | (0.374) | (0.374) |
| $N$ | 2597 | 2376 | 2962 | 2962 |
| adj. $R^2$ | 0.484 | 0.496 | 0.470 | 0.470 |
| Bank FEs | Yes | Yes | Yes | Yes |
| Month FEs | Yes | Yes | Yes | Yes |
| Cluster FEs | Yes | Yes | Yes | Yes |
| Cluster-Month FEs | Yes | Yes | Yes | Yes |

N.B.: The table shows the post-regulation monthly estimates from the event study model of equation(1). The dependent variable is the number of outstanding loans). The estimate in column(1) and column (2) is for short event windows while Column (2) and Column (4) present the result for longer event windows, The standard errors clustered at the bank level are in parentheses. *p $<$ 0.10, **p $<$ 0.05,***p $<$ 0.01