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Firm-level Perspective of Thailand's Low Investment Puzzle

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Abstract

Private investment in Thailand has been standing at a low level since the aftermath of the Asian Financial Crisis until present. Using firm-level data of virtually all registered firms in Thailand during 2001-2013, this paper finds that more than 60 percent of Thai firms have been undertaken negative net investment (invested at a rate slower than the depreciation rate) each year. Our regression results suggest that small firms and large firms have been facing different kinds of obstacles that ultimately led to persistently low investment at the aggregate level. For large firms, low or negative net investments are driven mainly by weak growth prospects and future uncertainties. For small firms, their investments are more likely hindered by supply-side constraints (lack of access to external finance) and negative net investments are driven mainly by inefficiency.

JEL Classifications: E22, G30, O16.

Keywords: Firm-level Investment, Tobin's Q, Resource Misallocation, Thai Economy

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1 Introduction

The 1997 Asian financial crisis (AFC) casts a long shadow on the level of investment in Thailand. In contrast to overall economic growth that bounced back swiftly in the post-crisis period, share of investment (gross fixed capital formation) over real output has never fully recovered to the same pre-crisis level even after economic or financial fundamentals have significantly strengthened. During the pre-crisis boom, private investment represented approximately 40% of the GDP. The ratio, however, has lingering only at around 17% after the crisis. This prolonged low level of investment has remained a puzzle.

What has held back business investment in Thailand? Is the low investment pattern observed across all firms? Is it caused by a demand- or supply-side problem? And what can policy makers do if they want to revitalize investment activity in Thailand?

The pattern of low investment in Thailand has stayed for more than a decade suggests that it is not a short-run effect of the AFC, but rather a result of something more structural. From a policy perspective, it is important to assess whether investment sluggishness stems mostly from weak aggregate demand and outlook uncertainty, or supply-side financial constraints, as these imply different policy responses. If the problem stems from the demand-side, i.e. firms delay their investment decision due to weak demand for their products or fears of future uncertainty, policy should focus on product market diversification, increasing investment incentives (e.g. investment tax credit), or boosting investors' confidence. On the contrary, if the problem stems from supply-side, firms do want to invest but they face some constraints such as labor shortage or financing constraints that hold back their business expansion, then incentives like tax credit would not help and it would be more effective for policy makers to focus on tackling the specific supply-side constraints.

While past studies have examined the post-Asian crisis investment (decline), not many of them have explored the issue from a firm-level perspective.[1] Using a comprehensive nation-wide firm-level dataset provided through Corporate Profile Financial Statement (CPFS) database,[2] we find a striking fact that more than 60% of Thai firms each year during 2001-2013 have undertaken negative net investment![3]

[1] See Zhou (2013), Barkbu *et al* (2015)

[2] The dataset obtained from Bank of Thailand database, which provide a data for comprehensive-registry and financial information of business in Thailand based on document officially submitted to the Ministry of Commerce.

[3] Note that firm-level data here allow us to construct only "investment net of depreciation". As such, it is possible to have positive gross investment after adding back depreciation cost. Morever, Thailand is not alone to have negative net investment. Comparing to other countries firm-level data, with similar definition of disinvestment and more or less similar period of the study (2001-

This means more than half of Thai firms do not invest enough to keep up with the rate of depreciation.

Negative net investment can have three interpretations: (1) gross investment is positive but below depreciation cost; (2) no new investment thus gross investment is zero; (3) firms sell off their assets so gross investment is negative. Given the widespread pattern of negative net investment observed at the firm level, understanding the underlying reasons for this phenomenon will be key to understanding the investment slump in Thailand.

Applying a structural vector autoregression (SVAR) method to aggregate-level investment and output data, we find that a decline in productivity shocks may explain the persistently low investment growth in recent period. We then turn to test this productivity shock assumption at the firm-level using the above mentioned dataset and identify the type of firms as well as the constraints they face that has contributed to low productivity and low overall investment in Thailand.

Our main finding is that small firms and large firms have been facing different kinds of problems that have ultimately led to persistently low investment observed in Thai economy since the Asian crisis. Small firms, which are the majority of Thai firms, face more of the supply-side problems. Some of the small firms are not productive or efficient enough so that they have to undergo a period of disinvestment, either to restructure their operation or before they leave the market altogether. Other small firms that are relatively more efficient are constrained by lack of external financing that holds them back from investing more. On the other hand, the demand-side problem could be at work to some extent for large firms which are typically do not have financial access problems.

This paper has makes the following contributions to the existing literature. First, this is the first paper to investigate the issue of Thailand's low investment at a disaggregated level that covers virtually all firms under the Ministry of Commerce's company registry system. This allows us to identify more precisely what determines or holds back investment specifically for different types of firms. Second, we test the theory of Tobin's Q with the comprehensive dataset of which a large number of firms are not stock listed companies. [4]

Additionally, this paper proposes a method to overcome one shortcoming of the CPFS firm-level balance sheet dataset which is the lack of labor-related data, such as wage and employment at the firm level. Annual CPFS dataset and the

2007): proportion of disinvesting firms are 31% in China (Ding *et al.* 2010); 22% in the UK (Bureau Van FAME dataset); 9% in Poland, 9% in Czech, 13% in Bulgaria, 33% in Romania (Amadeus dataset, Bureau Van Dijk).

[4] Among existing literatures, the lack of market valuation for non-stock listed firms makes the calculation of Tobin's Q for these firms not feasible using publicly available data.

monthly individual-level Labor Force Survey (LFS) data are combined from different frequencies. This data merging is done for the purpose of constructing firm-level total factor productivity, which will be used when we test different hypotheses explaining low or negative investment at the firm level.

The rest of this paper is organized as follows. We first review previous studies in Section (2). Section (3) describes Thailand's investment puzzle at the macro-level as a motivation of this paper. Moving on to the firm-level data, summary statistics and stylized facts are provided in Section (4). In Section (5), we perform various empirical analyses at the firm-level to identify the problems faced by different types of firms that may have led to low overall investment in Thailand. Section (6) concludes.

2 Related Literature

There exist a large body of literature on firm investment and most of the studies are based on the theory of Tobin's Q. Tobin's Q theoretical model relates firm-level investment rate to the ratio of the shadow value of capital and the unit price of investment goods. The shadow value of capital is an unobserved forward looking function of future expectations, captured by Tobin's Q. According to the theory, investment is supposed to be explained solely by Tobin's Q. However, reality often does not support the theory. Cash flow and cash stock are found to have large predictive power on investment even after controlling for Tobin's Q, indicating that capital market is imperfect and there may exist financial frictions which make investment deviate from what is predicted by the theory.

A common problem in testing Tobin's Q theory with the real world firm-level data is that it is hard to measure Tobin's Q directly and most of the time it is not readily available. Therefore, almost all of the previous studies used only stock-market listed companies of which the Tobin's Q is provided. The findings and conclusions from these studies are, thus, dominated by large firms which are not representative of the firm population. In the case of Thailand, listed companies cover less than 10 percent of the countrywide companies and are clearly not the representative of the whole country.

Some previous studies on the low investment puzzle in Asia have been done through the lens of cross-country firm-level data. Zhou (2013) used the Worldscope annual firm-level data[5] during 1991-2007 of the three Asian crisis countries: Indonesia, Malaysia, and Thailand to study post-crisis investment puzzle. By separating

[5] Worldscope database covers only the listed firms.

firms into tradable and nontradable group, Zhou found that investment slump was concentrated in the nontradable sector which was relatively more financially constrained compared to the tradable sector.

As for the literature on Thailand's investment, previous study has explored the low investment puzzle using both the macro-level data and the stock-listed firm-level data. Mallikamas *et al.* (2003) has explored what could be done to enhance private investment, using a listed firm-level data from 1995Q4 to 2003Q1. They conducted the firm-level regression based on the theory of Tobin's Q. Using the quarterly stock-listed firm-level data, they found that Tobin's Q seemed to lead to higher growth of private investment in subsequent quarters. This led to the implication that private investment could possibly accelerate in the near future as all key factors were pointing in that direction.

The issue of negative net investment (or disinvestment), on the contrary, has not been studied extensively. Ding *et al.* (2010) has nicely reviewed the finance literature and highlighted six major reasons for negative investment: (1) efficiency hypothesis: assets are likely to be sold or firms are less likely to invest when firms are less efficient than their industry benchmark ; (2) focus hypothesis: negative net investment make firms able to focus more on core activities; (3) financing hypothesis: firms sell off assets to raise capital; (4) liquidity hypothesis: there is higher probability of negative net investment in an industry with a liquid market for assets; (5) defensive restructuring hypothesis: firms sell off assets as a result of rapid economic transition; (6) slow growth hypothesis: firm sell off assets as they have slow growth. Ding *et al.* (2010) also conducted panel data probit estimation using Chinese firm-level data and found that negative investment by state-owned firms was explained by inefficiency while that of private firms are explained by financial constraints.

3 Thailand's Investment Puzzle

3.1 Macro Evidence

Macro-level time-series evidence shows that private investment in Thailand has been standing at a low level compared to the pre-AFC level (Figure 1, quarterly private investment over GDP). The decline in investment after the crisis was in part expected as a sharp correction of the earlier over-investment that was unsustainable. During the pre-crisis boom, private investment represented approximately 40% of the GDP. The ratio, however, has lingering only at around 17% after the crisis.[6] However, looking at the yearly data dated back further (Figure 2), it is evident that the current level of investment is also low relative to this longer perspective. *Chain Value Method (CVM)* to *Laspeyeres Fixed Method*, the revised quarterly fixed method data is only available back until 1993. Annual data based on the old CVM method is shown in Figure 2 to provide a general picture before 1993 or pre-boom period.

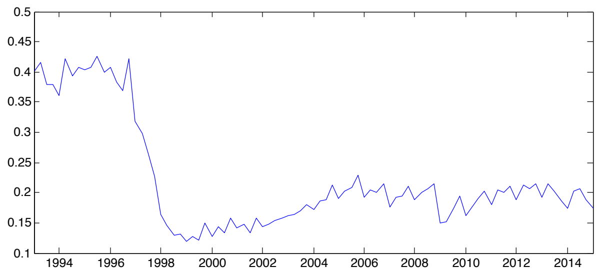

Figure 1: Gross investment over GDP (New Laspeyeres method): 1993Q1-2015Q1

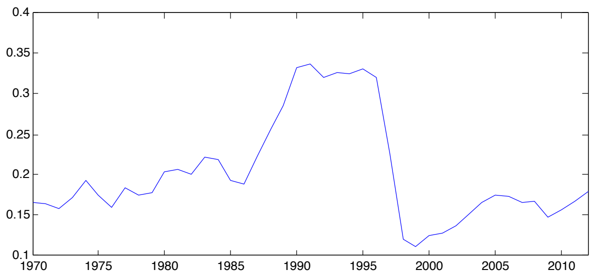

Figure 2: Gross investment over GDP (Old CVM method): 1970-2012, annual data

The question arises whether the low "aggregate" investment level reflects structural change or a result of some type of disturbances or shock to investment. If the latter prevails, which type of disturbances has caused investment to stagnate.[7] We will explore this question in the next subsection.

3.2 Sign Restriction SVAR Evidence

This section provides further evidence that the low level of investment could be a structural problem, caused by a permanent decline in productivity shock. A bivariate structural vector autoregression (SVAR) of investment

[6] *Aggregate country level* net investment has similar pattern with gross investment and is also positive; however, negative net investment does exist at *aggregate sectoral level* (See Appendix A).

[7] Cheunchoksan *et al* (2008) argued that to bring back Thai economy to the full capacity growth, the appropriate level of investment share in total output should be at 26 percent (the 2014 level was at 17 percent)

growth and output growth is constructed. The SVAR identified by decomposing the structural shocks according to the Neoclassical theory of investment into two types of sign restriction: (1) shocks to the marginal product of capital and (2) shocks to aggregate production function. Full description of model specification and other technical details are presented in Appendix B.

The first type of shocks (ϵ_1), shocks to marginal product of capital (MPK) or the relative cost of capital, is likely to affect the level of investment and output in the opposite directions, thus reducing the correlation among investment and output.

Examples of shocks to marginal product of capital can be oil price shocks: a plunge in global oil price may improve the level of investment while reducing the level of output. A change in minimum wage policy is another prime example of this types of shocks, which is particularly relevant in the recent Thai context. The effect of the increased minimum wage can have two possibilities. First, it is possible that a higher minimum wage lowers the cost of capital relative to labor, resulting in an increase in capital investment even output falls. The other possibility could be that setting a higher minimum wage increases overall investment cost, thus reducing investment and output. This depends closely on firms' degree of substitutability between labor and capital.

The second type of shocks (ϵ_2), shocks to aggregate production function, which affects the level of investment and output in the same direction, thus increasing the correlation among the two variables.

This type of shocks include technology or total factor productivity shock, labor supply shock, or a shift in resource allocation towards more efficient firms (creative destruction). Such positive productivity shocks lift long-run level of investment and output, and thus are more favorable to long-run economic growth than the first type of shocks.

To study the dynamics of aggregate investment in Thailand, we decompose the variance of investment growth into these two broad categories of underlying shocks. These sum to one by construction, thus we can draw the conclusion only in terms of relative contribution of each type of shocks to the total variance of the system, and not in absolute term.

The variance decomposition of shocks to investment in Figure 3 suggests that Thailand's investment may have experienced a decline in productivity shocks (relative to the other type of shocks) since 2001 on-

wards.[8] Prior to 2001, productivity shocks have been a dominating factor driving investment growth relative to shocks to MPK.

This implies that prolonged investment sluggishness might have been the result of a reduction in positive productivity shocks,[9] which could be due to lack of technological advancement, a stall in labor quality improvement, or capital misallocation. The downward trend in capital productivity index is shown in Figure 4. We will turn to a more in-depth analysis on this issue using firm-level data in section 4.

Figure 3: Variance decomposition of shock on investment. Horizontal axis is the ending period of the 5-year rolling regression.

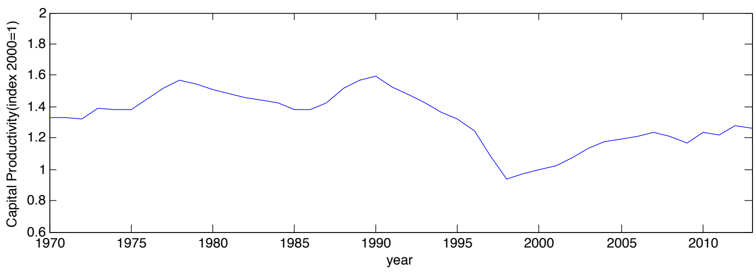

Figure 4: Capital productivity Index. Source: Asian Productivity Organization(APO) database.

[8] This will be year 2006 in the horizontal axis of Figure 3 as it represent the ending period of the five year rolling regression

[9] There also exists another possibility, which is an increase in negative MPK shocks. We, however, believe this case is less likely than a decline in overall positive productivity shock as this finding is consistent with the downward trend of capital productivity index (Figure 4).

4 Firm-Level Data and Stylized Facts

This section examines firm-level data in an attempt to gain deeper understanding of the low investment puzzle. Balance sheet information of Thai firms reveals a striking fact that a large share of the existing firms has undergone many years of negative net investment, especially for small firms. Simple stylized facts also suggest a possibility that financing constraint faced by individual firms may have been a cause of the sluggishness in overall investment.

4.1 Data and Sample

The annual firm-level data used in this paper is from Thailand's Ministry of Commerce through Corporate Profile Financial Statement (CPFS) database. The dataset contains financial information of all registered firms in Thailand, approximately 300,000 firms each year. The data is an unbalanced panel constructed from cross-sectional data each year from 2000 through 2013.[10] Firms are categorized into 18 major industries (first digit of ISIC classification), following 4 digit ISIC Rev.4 classification.

As the amount of investment variable is not provided in the CPFS database, we construct an investment variable as "net investment" or a change in the level of fixed capital (property, plant, and equipment) from the previous period.[11] By construction, firms need to survive for at least 2 consecutive years to be included in the data sample.

As investment here is net of depreciation, zero investment thus means firms invest just enough to offset depreciation. For negative net investment, there are two possible explanations: first, firms do not invest enough to keep up with depreciation; second, they sell off their assets.

We drop firms with zero fixed capital in the last period,[12] and those with reporting errors. For internal consistency of the balance sheet and income statement information, we construct several financial ratios.[13] To eliminate extreme values and outliers, we drop observations with each financial ratio falling below 0.1 percentile and above 99.9 percentile of the distribution in each year. If the ratio is bounded

[10] Data from year 2000 data is used only as the capital at the beginning of year 2001 to calculate 2001 investment, and as a normalizing year for the regression analysis.

[11] This follow closely from the standard capital accumulation equation $K_{t+1} = (1-\delta)K_t + I_t$ By transformation, we get $\frac{I_t}{K_t} = \frac{(K_{t+1}-K_t)}{K_t} + \delta$. Therefore, $\frac{(K_{t+1}-K_t)}{K_t} = \frac{I_t}{K_t} - \delta$, investment net of depreciation

[12] After data cleaning, there is no firm with zero fixed capital at each period of time, thus, eliminating firms with -100% net investment.

[13] Detailed description on the calculation of each financial ratio is provided in Appendix C.

below by zero, we drop out only those above 99.9 percentile in each year. The considered period is constrained to be only post AFC as the database is availability only from that point.

4.2 Stylized facts by firm size

Firms' sizes are categorized into three size groups according to the Ministry of Industry's classification: (1) small firms (book-value of fixed capital stock below 50 million baht), (2) medium firms (book-value of fixed capital stock between 50 million baht and 200 million baht), and (3) large firms (book-value of fixed capital stock greater than 200 million baht).

The majority of Thai firms are of small size (Table 1). All together small firms occupy a significant share of total investment and about 10% of total capital share relative to total capital of all firms (Figure 5.a).

It is worth noticing from Table 1 that while the number of small firms significantly increased from 2001 to 2013, its capital share has shown a downward trend or stable at best (Figure 5.a). This points to the fact that small firms must be disinvesting on average during this period. On the other hand, the number of large firms is increasing along with an increase in its capital share.

Looking at investment to output across all firms, Figure 5.b shows that median investment is low for the groups of medium and large firms, and negative for small firms.

Size-weighted-average investment is negative, driven by small firms negative net investment. The three groups also establish large variation in total asset growth (Figure 5.c). These differential characteristics by size underline the importance of including firm size as a control variable when conducting regression analyses.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Small	135,722	117,348	113,882	122,512	166,229	170,631	183,237	202,410	208,584	212,938	221,634	229,888	213,874
Medium	4,805	5,204	5,310	5,863	6,485	6,679	7,075	7,902	8,156	8,475	8,473	8,965	9,035
Large	2,345	2,780	2,800	3,011	3,301	3,394	3,634	4,136	4,280	4,434	4,427	4,828	4,957
Total	142,872	125,332	121,992	131,386	176,015	180,704	193,946	214,448	221,020	225,847	234,534	243,681	227,866

Table 1: Number of firms

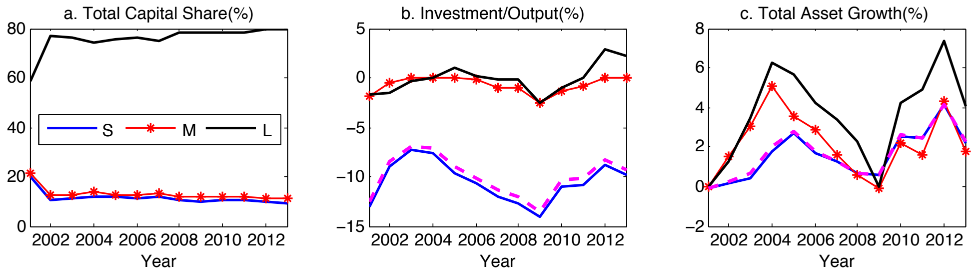

Figure 5: Selected financial ratios by firm size S-M-L: 2001-2013 Note solid blue line: small firms, starred red line: medium firms, solid black line: large firms, dashed pink line: size-weighted average median.

One remarkable revelation when examining the level of investment across firms is a large share of firms with negative net investment. More than 60 percent of Thai firms have negative net investment each year throughout the period under study (Figure 6.a). This is the fact that will be missing if we were to consider country-level net investment data alone. Similarly, if we first add up the firm-level fixed capital stock to the country-level each year and then calculate net investment, the adding-up net investment will become positive just like in the macro data and the pattern of negative net investment will be dissipate. Therefore, we are able to argue that negative net investment data found here is not the a result of misreporting and will be positive similar to the adding up country net investment.

Interestingly, the high number of disinvestment firms persists not only in small size firms, but medium and large firms as well (Figure 6.b) . Comparing across the three groups, the group of small firms has the highest share of disinvesting firms, and the highest median level of negative net investment (Figure 6.c). Large number of disinvesting small firms is consistent with the fact that small firms total investment is below those of the medium and large firms.

This stylized fact for Thai firms is striking when compared to other countries. Ding *et al.* (2010) has shown that despite high aggregate country-level investment and great economic growth in China, negative net investment is found at the firm level at around 31% of firms each year. In United Kingdom, 22% were disinvested according to UK FAME dataset (Bureau Van Dijk); 9% in Poland, 9% in Czech, 13% in Bulgaria, 33% in Romania are disinvested according to Amadeus dataset (Bureau Van Dijk).

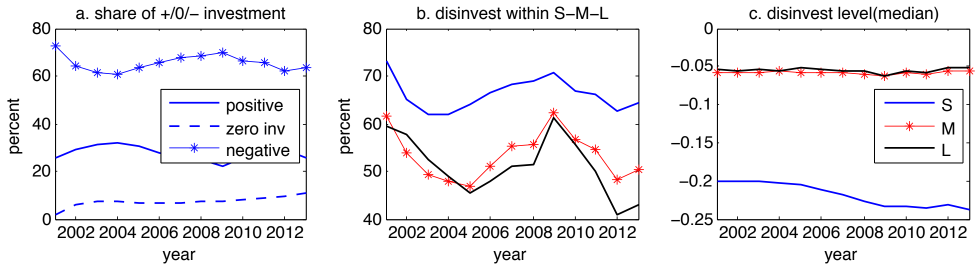

Figure 6: (a.) Share of firms with positive, zero, and negative net investment each year. (b.) Share of firms that have negative net investment within S-M-L group. (c.) Median level of negative net investment of each size.

Comparing financial ratios, they seem to suggest that positive net investment firms are more efficient than negative net investment firms. Efficiency ratios (proxied by asset turnover ratio (Figure 7.a), operating profit margin (Figure 7.b), and return on asset (Figure 7.d) are clearly lower for negative net investment group compared to positive net investment group. In addition, weighted average median of leverage ratio for negative net investment group is lower than positive net investment group. And current ratio or liquidity ratio of negative net investment group is higher than the other group.

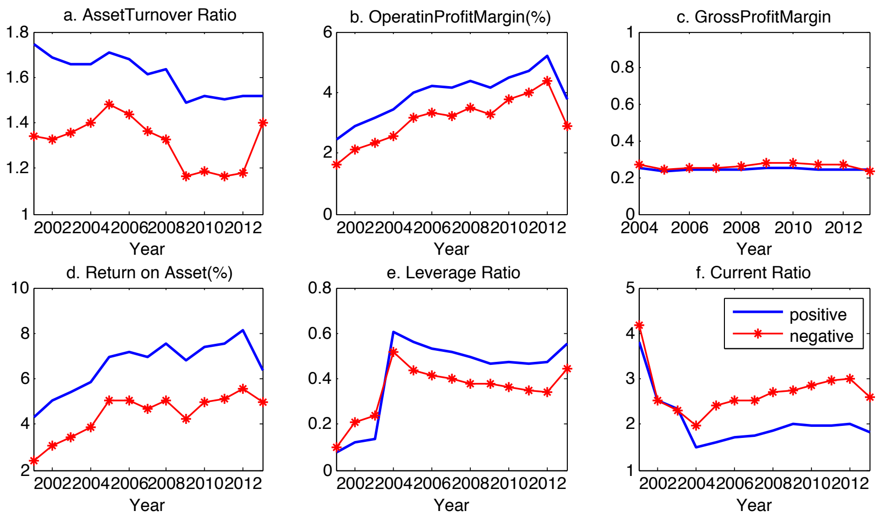

Figure 7: Selected financial ratios (weighted average median among firm's size S-M-L): 2001-2013

Note (1) solid blue line: positive net investment firms; starred red line: negative net investment firms.
(2) Gross Profit Margin report here covers year 2004-2013 as the data for *cost of good sold* prior to 2004 might not be accurate.
(3) The 2004 increase in the leverage ratio is due to increase in total debt of large firms in sector E. Electricity, gas, and stream (also the reason for drop of current ratio). This will not bias out result when doing the regression as all variables in the regression will be transformed into logged form in the way that preserves each variable' conventional meaning of the Tobin's Q model.

However, summary statistics below show some evidence that small firms are not always less productive compared to medium and large firms.

This statement holds for both positive net investment and negative net investment groups. Data on firm efficiency are provided in Figure 8-11.

• For both positive net investment and negative net investment groups, small firms' median asset turnover ratio is the highest compared to medium and large firms (Figure 8). Asset Turnover Ratio is sales over total asset. This tells how much total asset can generate revenue from sales.

• For both positive net investment and negative net investment groups, it is likely that small firms have higher startup or fixed cost, reported as sales general and administrative expenses (SG&A) Although operating profit margin of small firms is clearly the lowest compared to medium and large firms (Figure 9), its gross profit margin is the highest among all three sizes (Figure 10). Small firms' lower operating profit margin is perceivable as small firms typically have less market power and less profit generating abilities. Higher gross profit margin despite lower operating profit margin of small firms, however, suggests that small firms have higher SG&A expenses, perhaps due to the expansion of business into new markets, but their revenue from sales are not necessarily lower.

• Small firms with positive net investment exhibit return on assets that is on average higher than the larger firms (Figure 11: left panel). Return on asset (ROA) is the product of operating profit margin and asset turnover ratio. In this case, small firms high ROA is driven mainly by high asset turnover ratio. Again, this indicates that small firms with positive net investment are likely to use their assets efficiently so that (despite the lower profit generating ability) their return on assets is higher than that of larger size firms. This is, however, not the case for small firms with negative net investment.

• Small firms with negative net investment's return on assets are lower than that of the bigger sized firms on average (Figure 11: right panel): although small negative net invested firms use their assets more efficiently than medium and large firms, it is not efficient enough to cover the lower profit generating ability, making their return on assets lower than those of the larger size firms most of the period.

This could be better explain by looking at asset turnover ratio in Figure 8. Although asset turnover ratio of small firms within the negative net investment group are higher than medium and large firms, it is not high enough compared to small firms in the positive net investment group. This highlights the fact that, although small firms are more efficient than medium and large firms within the negative net investment group, it is not efficient enough (compared to small firms in the positive investment group) to be able to increase investment or have positive net investment.

It is worth noticing here that, even though asset turnover ratio of small firms in the negative net investment groups are below those of small firms in the positive net investment group, it is above those of medium and large firms in the positive net investment group (Figure 8). The fact thus shed light to the possibility that it is harder for small firms to overcome market competition, increase net investment from negative to positive level, compared to larger size firms.

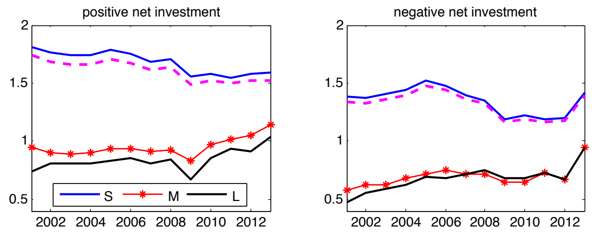

Figure 8: Asset Turnover Ratio (median) by firm size S-M-L

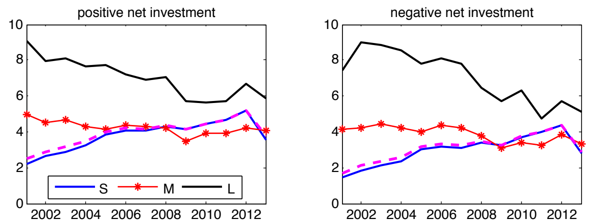

Figure 9: Operating Profit Margin (median, in percentage unit) by firm size S-M-L

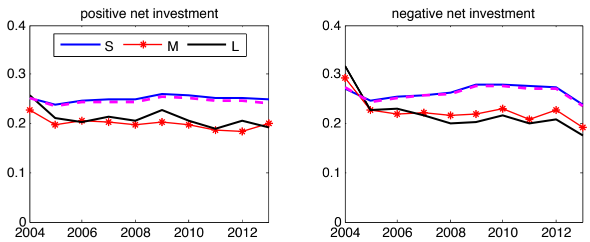

Figure 10: Gross Profit Margin (median) by firm size S-M-L

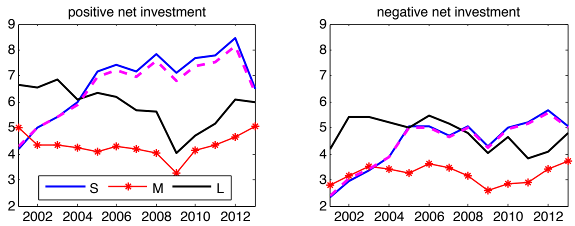

Figure 11: Return on Asset (median, in percentage unit) by firm size S-M-L

Looking at capital structure, it appears that small firms may face

greater external credit constraint and tend to rely more on internal finance.

• Considering the leverage position, small firms have lower leverage ratio than medium and large firms (Figure 12). On the one hand, this could be interpreted as more conservative approach to debt financing practiced by small firms. On the other hand, it could also be explained by a more limited access to external finance, which is likely to be the case for small firms in an environment where there exist frictions in the financial system.

• Considering the liquidity condition, small firms on average have higher current ratio compared to medium and large firms (Figure 13). One possibility is that small firms may have to maintain internal liquidity since they have limited access to external finance. It is thus worth exploring further if financing constraint is a problem holding back investment in Thailand especially among small firms.

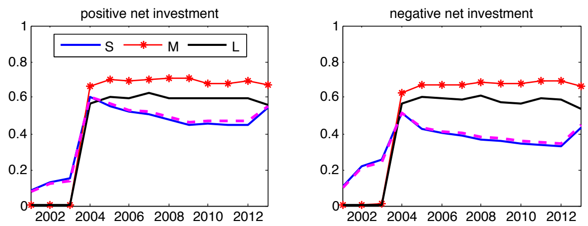

Figure 12: Leverage ratio (median) by firm size S-M-L

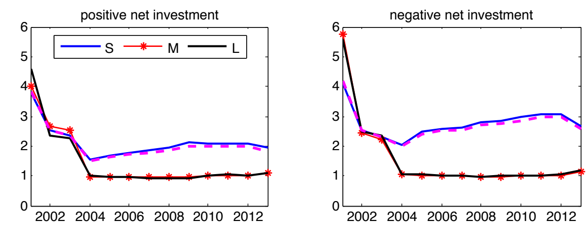

Figure 13: Current ratio (median) by firm size S-M-L

4.3 Stylized Facts by industry

The sample firms are separated into 18 industries according to ISIC-rev 4 classification. Detailed description of each industries are described in Appendix D.1

Investment (capital growth) is low in some particular industries; however, their return on asset is not so low. The median of the capital growth of the following industries: construction, wholesale and retail trade, transport and storage, professional and science, other services, is below the total weighted average median almost the entire period of the study (Figure 14.a). Interestingly, return on asset of these industries is not that low (Figure 14.b). Their median remains well above the weighted average median return on asset throughout the period. This suggests that low investment industries might not be less efficient.

Heterogeneity across industries also suggests that we need to control for industry group when performing the regression analyses.

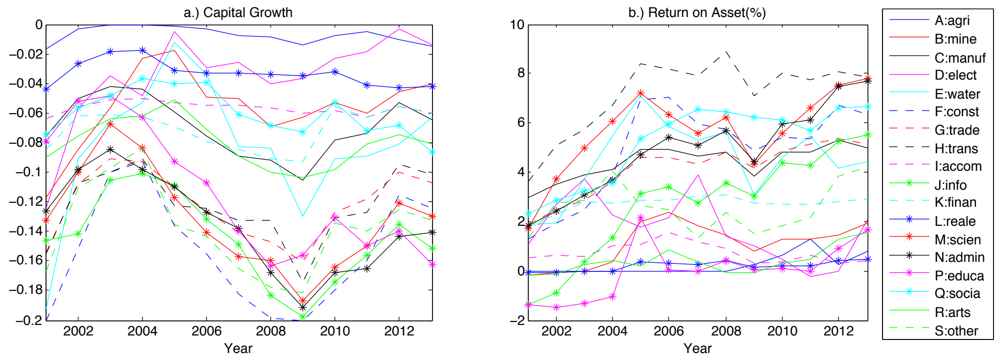

Figure 14: (a.) Investment (capital growth) by industry (b.) Return on asset by industry

5 Identifying Capital Misallocation from the Firm-Level Perspective

The previous section points to a potential problem of inefficient capital allocation that may have led to persistently low investment in Thailand. We will explore this issue more closely in this section.

5.1 Dispersion (s.d.) and Level (median) of MRPK

As predicted by a standard theory on resource allocation, well-functioning capital markets should allocate capital in the way that the marginal revenue product of capital (MRPK) is equated to the marginal cost of capital, i.e. market interest rate. If this is the case, then we should expect the dispersion of MRPK to be small. In other words, an increase in the dispersion of MRPK across firms could reflect increasing barriers to the efficient allocation of capital (Hsieh and Klenow (2007)).

MRPK here is measured as operating profit over fixed capital at the beginning of the period.[14] Figure 15 below shows the evolution of the industry-share-weighted average dispersion of MRPK. The dispersion in the first year is normalized to 1. Following Gopinath *et al.* (2015), the calculation is done in two steps. First, we

[14] Detailed derivation of the precise formula of MRPK equation is shown in Appendix G.

calculate a given dispersion of log MRPK across all firms in a given 1-digit ISIC industry each year. Second, the yearly industry-specific dispersions are weighted average by industries' time-invariant weights, which are the average of the capital share in each industry across time. Using the time-invariant weight is appropriate here as the actual weight has rarely changed each year. Therefore, the variation of the overall MRPK dispersion here is from changes of dispersion within 1-digit-ISIC industries over time.

The dispersion of MRPK across firms within the same 1-digit ISIC industry appears to be increasing over time. One possible explanation could be capital misallocation that has become more intensified.[15] Figure 15 shows a clear increasing trend in the dispersion of log MRPK over the considered period. It should be noted that the dispersion does not increase much after the Asian Financial Crisis but the trend starts to increase in an accelerated speed after the post 2007/2008 global financial crisis (GFC). This suggests that there were some frictions in the financial or capital markets that have emerged or become intensified after the 2008 GFC that have given rise to a more severe capital misallocation.

To account for a potential bias due to an increase in the number of firms in the sample each year, we also present the dispersion of a "balanced sample" of firms that survive throughout the whole period under the study. The balanced sample consists of approximately 40,000 firms each year. Not surprisingly, the dispersion of the "full sample" increases more rapidly from 1 to 1.6, compared to 1.25 for the "balanced sample". In any case, it is clear that the dispersion from both samples shows an increasing trend which possibly reflects deteriorating allocation efficiency. Note here that, this increasing trend in dispersion is also observed across all individual industries.

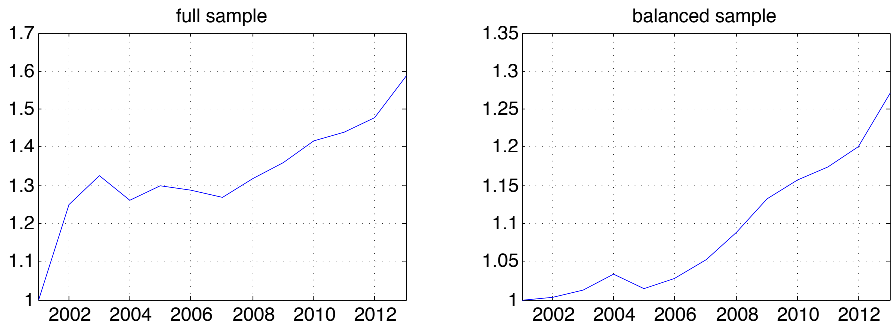

Figure 15: Industry-share-weighted average dispersion of log MRPK at 1 digit ISIC industry from 2001-2013, normalized by the beginning of period data (2001)

[15] Another explanation of this large and increasing dispersion could be due to variations in the riskiness of firm.

The statistics we present above provide some evidence for a potential capital misallocation problem at a nationwide level. The question remains whether such problem occurs only at some particular groups (sizes and industries) that contributes to the large dispersion at the aggregate level.

To answer such question, we will compare the MRPK level (median) and investment across firm sizes and industries.

For the size aspect, MRPK (median) for small firms is clearly the highest among the three size groups (left panel of Figure 16) while, as shown in the previous section, their investment is the lowest among the three.

For the industry aspect, high MRPK (median) industries are the same group with those whose investments are below average (right panel of Figure 16). These industries include construction; wholesale and retail trade; transportation and storage; professional and scientific activities; administrative and support activities. It is puzzling as this evidence goes against a standard micro theory which would predict that firms with high MRPK (i.e. firms that have high productivity of capital) should obtain more capital and hence invest more than firms with low MRPK. Again, this points to a capital misallocation problem, especially for small firms and some particular industries specified above.

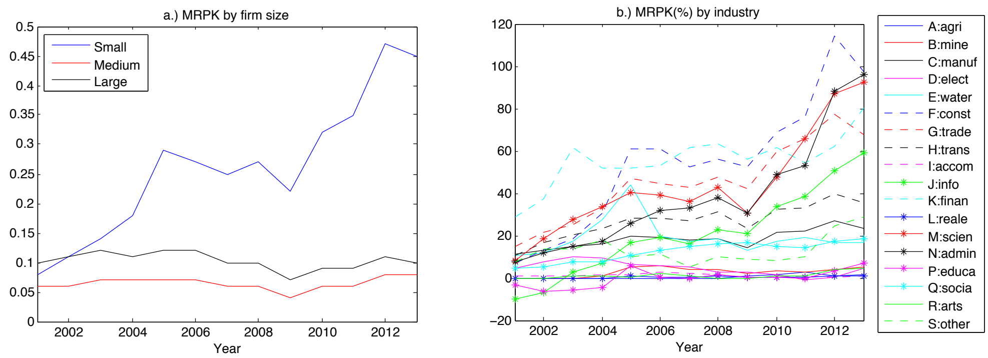

Figure 16: Median level of MRPK from 2001-2013

To deepen the analysis, we propose the following method to measure capital misallocation more meticulously within each size, at the 4 digit ISIC industry level:

Markets are supposed to allocate resources so that MRPK is equalized among firms within the same 4-digit ISIC industry. Using $\tau_{i,t}$ to summarize the effects of various capital market distortions or how much its MRPK is different from weighted average MRPK:

$$MRPK_{i,t} = (1 + \tau_{i,t})MRPK_{in,t} \quad (1)$$

where $MRPK_{in,t}$ is the weighted average marginal revenue product of capital within

4-digit ISIC industry. Weight here is the capital share within each 4-digit ISIC industry.

If $\tau_{i,t} > 0$, firms face unfavorable capital market distortions and the firm' MRPK is lower than its industry weighted average MRPK. On the other hand, if $\tau_{i,t} < 0$, firm faces favorable distortions and the firm' MRPK is higher than its industry weighted average MRPK. We calculate $\tau_{i,t}$ of each firm and show its summary statistics by firm' size below in Table 2.

The results below show that small firms face unfavorable capital market distortions at the 4-digit industry level while medium and large firms tend to face favorable distortions across time. From Table 2, we can see that though the medians of $\tau_{i,t}$ across firm size are not much different, the skewness of the distribution (comparing the mean with the median) is diverse. The distribution is left-skewed for small firms while it is right-skewed for large firms. This means that $\tau_{i,t}$ is higher for small firms and lower for large firms.

		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Small	mean	3.46	355	319	1,092	4,126	566	1,386	2,540	3,553	445	157,057	2,798	5,559
	median	-0.74	-0.97	-0.98	-0.93	-0.93	-0.90	-0.87	-0.84	-0.87	-0.94	-0.88	-0.93	-0.99
Medium	mean	-0.07	-0.24	-0.36	-0.96	-0.89	0.42	-0.40	-0.74	-0.44	1.04	-29.15	-1.94	-0.34
	median	-0.78	-0.98	-0.97	-0.93	-0.96	-0.98	-0.94	-0.93	-0.95	-0.97	-0.96	-0.98	-1.00
Large	mean	0.10	-0.43	-0.40	0.09	-0.31	-0.36	-0.14	-0.12	-0.75	-0.36	26.86	-0.27	-0.22
	median	-0.63	-0.91	-0.90	-0.75	-0.74	-0.92	-0.81	-0.83	-0.80	-0.88	-0.91	-0.93	-0.99

Table 2: Summary statistics of $\tau_{i,t}$ by firms size

It is plausible that small firms, even if they are relatively more efficient, do not have sufficient access to external finance thus face financing constraint which holds back their investment. To test this hypothesis and to be able to draw a causal relationship, we will turn to a panel data neoclassical investment equation regression in the next subsection.

5.2 Testing for Financial Constraint

5.2.1 Hypothesis & Model Description

In this section, we will test whether firms of some particular types face credit constraints that have hindered their investment decision.

An empirical study in this section is built upon the theory of Tobins Q. We employ a fixed effects panel data regression to account for several factors affecting investment at the firm level. The conventional model used is specified as follows:

$$ln\Big(\frac{K_{i,t}}{K_{i,t-1}}\Big) = \beta_1 ln\Big(\frac{CA_{i,t-1}}{K_{i,t-1}}\Big) + \beta_2\Big(\frac{NI_{i,t-1}}{K_{i,t-1}}\Big) + \beta_3 ln\Big(\frac{D_{i,t}}{D_{i,t-1}}\Big) + \beta_4 ln\big(Lev_{i,t-1}\big)$$
$$+ \beta_5 ROA_{avg,t} + \beta_0 + \alpha_i + \alpha_s + \alpha_t + \alpha_{in,t} + \epsilon_{i,t} \tag{2}$$

Variable	Description
$\{K_{i,t}\}$	private fixed capital stock (properties, plant, and equipment)
$\{CA_{i,t}\}$	current assets (cash stock; cash and short term investments)
$\{NI_{i,t}\}$	net income
$\{D_{i,t}\}$	total debt
$\{Lev_{i,t}\}$	leverage ratio (total debt over total asset)
$\{ROA_{avg,t}\}$	average three-year return on asset or $[ROA_t + E_t(ROA_{t+1}) + E_t(ROA_{t+2})]/3$

α_i, α_s, α_t capture firm-, size-, and time-fixed effects, respectively, while $\epsilon_{i,t}$ is the error term. The error term here is modeled as clustered standard error at the firm level; thus, assuming independence across clusters but correlation within clusters. To control for industry-specific changes in investment opportunity that could effect investment decision, the interactions of time dummies and 4-digit ISIC industry dummies are added $\alpha_{in,t}$.

As the dataset is very large and highly skewed,[16] we will log-transform some variables that always have positive values, including capital, current asset, and leverage ratio. Working with the natural log of the positive-value variables makes their distribution more normal and the mean closer to the median, thus making the regression results more robust. Some variables are normalized by the beginning of the period fixed capital stock.

The above equation is a modified version of the standard neoclassical investment model in which investment or natural log of capital over capital at the beginning of the period on the left hand side [17] is linked to *(1) expected profitability*, *(2) inside liquidity*, and *(3) outside liquidity* on the right hand side.

Expected profitability here is captured by three-year average (with two-year ahead and current) return on asset instead of Tobins Q. Three-year average ROA is used instead of Tobins Q because Tobins Q data is available only for stock market

[16] Distribution of selected variables included in the regression are provided in Appendix D.

[17] Note here that we are able to construct *net* investment but are unable to construct *gross* investment as fixed capital reported in the dataset is already net of depreciation and the depreciation rate is unprovided.

listed companies, and not for non-listed firms.[18] The assumption made here is that firm has perfect foresight, thus, can perfectly foresee their future profitability. $E_t(ROA_{t+n}) = ROA_{t+n}$ where $n > 0$. Note that, by construction of the main variables, firms need to survive for at least four consecutive years to be included in this analysis.

Inside liquidity or firm's internal finance is captured here by cash flow and cash stock variables. Here, a proxy for cash flow is net income over initial fixed capital at the beginning of the period $(\frac{NI_{i,t}}{K_{i,t-1}})$.[19] Net income normalized by capital at the beginning of the period here is used as an imperfect measure of cash flow from operation as it is highly correlated with the actual cash flow and the precise data on cash flow is not provided. Notice here that net income does not present here in the natural log form as the it contains both positive and negative values; thus, the magnitude of the effect will be different than other logged variables when reading the results. Cash stock is captured by current assets normalized by initial fixed capital $(ln(\frac{CA_{i,t}}{K_{i,t-1}}))$. Current asset provided in the dataset include cash stock, cash, and short term investments.

Outside liquidity or external financing is captured by debt stock or leverage ratio $(ln(lev_{i,t-1}))$ and debt flow or debt growth $(ln(\frac{D_{i,t}}{D_{i,t-1}}))$.

For financially constrained firms, we expect a significantly positive relationship between capital growth (investment) and inside liquidity variables, which would imply that firms were unable to obtain external finance and thus had to rely mainly on internal liquidity in driving investment.

To better compare differential effects of each factor across firm sizes, all the main variables in the model, internal-external finance and the three-year average return on asset, will be multiplied by $m-1$ size dummy variables (m is the number of size classification: if S-M-L classification is used, m=3 ; if decile classification is used, m=10) to capture the differences across sizes. In the analysis where size classification follows S-M-L, dummy $I_s = 1$ when s = medium, large; and zero otherwise.[20]

The model will become:

[18] Our proxy for Tobins Q is consistent with Abel and Blanchard(1986). They explored an alternative measure of Q by forecasting future marginal revenue products of capital and future discount rates to estimate the expected present discounted value of profit.

[19] Net income here is used as imperfect proxy of cash flow hypothesis as the exact cash flow from operation data is unprovided. Therefore, we are unable to uncover the exact cash flow data; however, cash flow and net income are believed to be highly correlated; thus, this is the best methodology we proposed.

[20] For the size decile classification, $I_s = 1$ when s = decile 2, decile 3,...decile 10

$$
\begin{aligned}
ln\Big(\frac{K_{i,t}}{K_{i,t-1}}\Big) = {} & \beta_1 ln\Big(\frac{CA_{i,t-1}}{K_{i,t-1}}\Big) + \beta_2\Big(\frac{NI_{i,t-1}}{K_{i,t-1}}\Big) + \beta_3 ln\Big(\frac{D_{i,t}}{D_{i,t-1}}\Big) + \beta_4 ln\big(Lev_{i,t-1}\big) + \beta_5 ROA_{avg,t} \\
& + \sum_s \beta_{1,s} I_s ln\Big(\frac{CA_{i,t-1}}{K_{i,t-1}}\Big) + \sum_s \beta_{2,s} I_s\Big(\frac{NI_{i,t-1}}{K_{i,t-1}}\Big) + \sum_s \beta_{3,s} I_s ln\Big(\frac{D_{i,t}}{D_{i,t-1}}\Big) \\
& + \sum_s \beta_{4,s} I_s ln\big(Lev_{i,t-1}\big) + \sum_s \beta_{5,s} I_s ROA_{avg,t} + \beta_0 + \alpha_i + \alpha_s + \alpha_t + \alpha_{in,t} + \epsilon_{i,t}
\end{aligned} \tag{3}
$$

Therefore, the marginal effect of each size will be β_{1s}, β_{1m}, β_{1l} [21]

The regression will exclude industry K (finance and insurance activities) and L (real estate, renting, and business activities) as these two industries have many observations with capital equal to zero, thus it may bias the regression results. Capital growth on the LHS of equation (3) is equivalent to the share of investment over GDP.[22]

We first regress the natural log of capital growth on three-year average ROA and the natural log of current asset over capital in the beginning of the period or "cash stock" as the baseline model.

For robustness check, we use an alternative proxy of internal finance; cash flow variable: "cash flow variable" which is measured by net income over capital at the beginning of the period. We next test for robustness of the internal liquidity results by including external finance: leverage ratio and debt flow over initial capital. We expect change the internal liquidity coefficients in the case that low investment is being held back by the level of leverage or, in other words, it is highly dependent on external debt flow.

5.2.2 Results for ***Pooled Sample***

This section presents the results of investment regression (equation 3) for all Thai firms, pooled sample.

Table 3 shows the results of the baseline model. Model 1 is the baseline model of which investment is regressed only on three-year average return on asset and internal finance. Model 2 is then augmented by controlling for external finance.

The results suggest the possibility that Thai firms are facing non-trivial credit constraint as internal finance, proxied by current asset over capital at the beginning of the period, can significantly explain investment and is large in magnitude.

[21] $\beta_{1s} = \beta_1$, $\beta_{1m} = \beta_1 + \beta_{1,medium}$, $\beta_{1l} = \beta_1 + \beta_{1,large}$.

[22] Distribution plots for selected variables are provided in Appendix D.3-D.5.

Variable	Small		Medium		Large	
	model 1	model 2	model 1	model 2	model 1	model 2
$ROA_{avg,t}$	0.031**	0.032**	-0.034**	-0.038*	-0.054**	-0.050**
$\ln(CA_{t-1}/K_{t-1})$	0.130**	0.148**	0.096**	0.140†	0.073**	0.143
$\ln(Lev_{t-1})$		0.015**		0.049**		0.072**
$\ln(D_t/D_{t-1})$		0.045**		0.025**		0.016**
constant	-0.147**	-0.096*	0.207**	0.256**	0.387**	0.462**

Table 3: Marginal effect of each size, recovered from equation 4, for pooled sample (1,524,113 observations: small= 1,426,355 observations; medium = 64,648 observations; large= 33,110 observations)

The results, however, can be biased as the behavior of firms with positive, negative, and zero net investment may be highly heterogeneous. To account for such differences, we will next present the results on sub-sample regressions. *Positive investment sample* will be separately analyzed in section 5.2.3 and *negative net investment* sample will be separately analyzed in section 5.2.4. Fixed-effect logit regression is used with *negative net investment sample* in section 5.3 to account for the nonlinear nature of firms' disinvestment threshold.[23]

5.2.3 Results for ***Positive Net Investment*** Sample

In this section, we consider the sample of only positive net investment firms.

The results from table 4 implies that the majority of Thai firms even with positive investment might also face credit constraint problems. From both model 1 and 2 we can see that current asset over initial fixed asset, which is used here to proxy financial or liquidity constraint, can significantly explain capital growth with the largest magnitude of more than 20 percentage point, other variables are of less importance.

Also, it is likely that small firms face more credit constraint than medium and large firms as the internal finance effect of the small firms is the largest: $(\beta_{1s} = 0.225) > (\beta_{1m} = 0.158) > (\beta_{1l} = 0.116)$. An F-test rejects the restrictions that the coefficient of internal finance and its interaction with the size dummies are significantly not different from zero.

[23] See Abel and Eberly (1994) for further theoretical discussion

Variable	Small		Medium		Large	
	model 1	model 2	model 1	model 2	model 1	model 2
$ROA_{avg,t}$	0.038**	0.057**	-0.276*	-0.276*	-0.286**	-0.306**
$\ln(CA_{t-1}/K_{t-1})$	0.225**	0.271**	0.158**	0.228**	0.116**	0.215**
$\ln(Lev_{t-1})$		0.064**		0.095**		0.116**
$\ln(D_t/D_{t-1})$		0.049**		0.02**		0.015**
constant	0.455**	0.451**	0.605**	0.631**	0.594**	0.683**

Table 4: Marginal effect of each size, recovered from equation 4, for invested sample (445,514 observations:small= 402,741 observations, medium = 27,437 observations, large= 15,336 observations)

For robustness of the results, we further separate the full sample data into 10 groups ranked by *decile of fixed capital* each year. This is due to variations which still remain within each of the size classification (S-M-L). Decile classification ranges from the smallest size (decile 1) to the largest size (decile 10). This will reduce the variability inside the very large number of small-sized firms sample.

Regression results with decile interactions of all major variables are reported in Appendix E. In Appendix E, model 1 and 2 use cash stock (current asset over capital) as internal finance. Model 3 uses cash flow or net income over capital at the beginning of the period as internal finance. Model 4 uses both cash stock and cash flow.

Appendix F shows that cash stock (natural log of current asset over fixed capital at the beginning of the period) performs better than cashflow using net income over fixed capital at the beginning of the period as a proxy of internal finance. This is consistent with several existing studies which had argued for the use of cash stock or current assets rather than cash flow as a measurement of financing constraint.[24]

Regression by decile shows that the larger the firms are (larger decile), the less credit constraint they face. This is shown as a downward trend of internal finance coefficient (left panel of Figure 17), which is the plot of model 2 coefficient for the recovered effect of internal finance for each decile. The results are robust for all models that use cash stock as a proxy for internal finance.

It is worth noting that, consistent with the previous section, the largest firms at decile 10 appear to be relatively inefficient : investment depends negatively on expected profitability proxied by three-year averaged ROA.

All industries, except industry D (electricities, gas, and stream),[25]

[24] For example, see Blinder (1988) comment on Fazarri *et al* (1988).

[25] Industry D (electricities, gas, and stream) shows a peculiar trend in Figure 17.b as it has

show less credit constraint trend as size quartile becomes larger. This can be seen from the recovered effects of internal finance for each size quartiles which are plotted in the right panel of Figure 17 (based on a regression of each 1-digit ISIC industry, with size quartile dummy interactions). Full results are reported in Appendix F. Here, we use *size quartile* instead of *size decile* classification as some small industry does not have enough observations for decile classification.

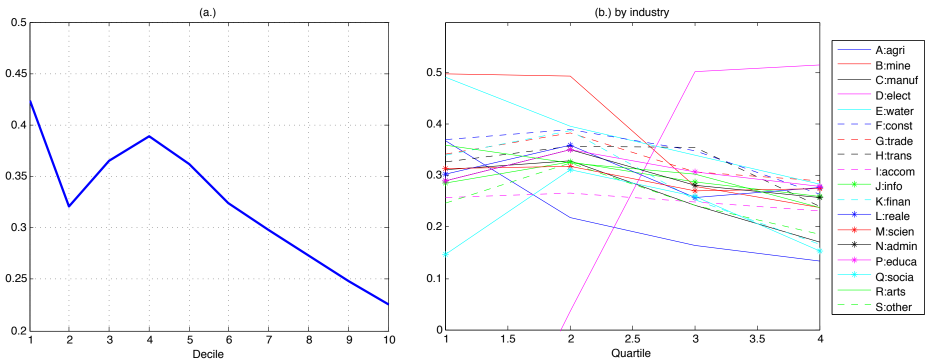

Figure 17: Recovered coefficients of $\ln(CA_{t-1}/K_{t-1})$ in equation 3. for each decile (on the left panel), quartile (on the right panel). Complete tables are in Appendix E and .

So far, we provide empirical evidence that supports the notion that financing constraint facing some firms (possibly resulted from capital misallocation) might be an important factor that hinders Thailands overall investment. And small firms, although they could be more efficient than large firms, are likely to face more financing constraint compared to large firms. These findings are based on positive investment firms. We will next turn to the sample of firms that have undertaken negative net investment.

5.2.4 Results for *Negative Net Investment* Sample

Be reminded that, due to data availability problem, we can construct only *net* investment, not the *gross* investment from the firm-level data set.[26] Although this does not pose a problem for the regression analysis, the interpretation of disinvestment (negative net investment) must be done with care. Disinvesment here has two possibilities: firms do not invest enough to keep up with depreciated capital, or firms sell off their assets.

the smallest number of observations compared to other industries. We believe the result might be driven by a few observations, and thus are less robust compared to other industries.

[26] Fixed capital reported in CPFS dataset is netted of depreciation and there is no precise depreciation cost reported, so we cannot add back depreciation to calculate gross investment.

The regression results by decile show signs of inefficiency as investment depends very little, or negatively, on Tobins Q. Moreover, it seems like there are other factors beyond financial constraint that may have held back investment for weak firms as internal and external finance factors can also explain very little of the investment level. Full results are reported in Appendix D.

Subsample regressions above (positive net investment and negative net investment sample) analyze only the linear form of investment function. However, a nonlinear form or the disinvestment threshold can arise in the case of disinvestment behavior.[27] To account for such non-linearities and to analyze more deeply into what explains firms' decision to disinvest, we will resort to a type of limited dependent variable (conditional logistic regression) model in the next section.

5.3 Why do many Thai firms have negative net investment?

5.3.1 Hypothesis and Model Description

According to the stylized facts presented in section 4.2, more than 60 percent of Thai firms have continued to disinvest over time. This section tries to address what factors affect firms decision to disinvest or to invest not enough to keep up with the depreciation cost.

To account for firm's threshold to disinvest, the model used in this section will be a type of limited dependent variable model: logistic regression with individual and time fixed effect.[28] Baseline model has the following specification:

$$\begin{aligned} Disinvestment_{i,t} = \beta_0 &+ \beta_1\Big(\frac{NI_{i,t}}{K_{i,t-1}}\Big) + \beta_2\Big(\frac{CA_{i,t}}{K_{i,t-1}}\Big) + \beta_3\Big(Lev_{i,t}\Big) + \beta_4\Big(\frac{\Delta D_{i,t}}{K_{i,t-1}}\Big) \\ &+ \beta_5\Big(ROA_{avg,t}\Big) + \beta_6\Big(ROA_{std,t}\Big) + \beta_7\Big(TAGrowth_{i,t}\Big) \\ &+ \alpha_i + \alpha_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

To test the probability of negative net investment (disinvestment), the dependent variable $Disinvestment_{i,t}$ is a binary variable taking the value of 1 if a firm has negative net investment, and 0 otherwise.

Independent variables here are grouped to three hypotheses of disinvestment

[27] See Abel and Eberly (1994, 2002) for further theoretical explanations.

[28] We aware that there might be other sample splitting point and modern techniques e.g. threshold panel regression are available (e.g. Hansen (1999)); however, such techniques are not easy to implement and require technical fluencies especially with large fixed-effect unbalanced panel data. Future implementations of such techniques are highly welcome.

decision[29]: *(1) financing hypothesis*, *(2) efficiency hypothesis*, and *(3) growth hypothesis.*

Under the **Financing hypothesis**, firms either do not have enough funding thus reduce their investment or they sell assets to obtain funds because external funds are expensive or unavailable. Relaxing credit constraint is one possible solution to helps firms exposed to this condition. The intuition is similar to section 5.2 capital growth panel data regression model. Independent variables under this hypothesis include net income over capital at the beginning of the period $\left(\frac{NI_{i,t}}{K_{i,t-1}}\right)$, current asset over capital at the beginning of the period $\left(\frac{CA_{i,t}}{K_{i,t-1}}\right)$, leverage ratio ($Lev_{i,t}$), and change in total debt over capital at the beginning of the period $\left(\frac{\Delta D_{i,t}}{K_{i,t-1}}\right)$.

Under the **Efficiency or Defensive Restructuring hypothesis**, firms do not invest enough to keep up with depreciation or they sell fixed assets when they are less productive than their industry benchmark. It is also possible that these firms have difficulties in adapting to new market environment, they face tough market competition and thus, in the period of adjustment, need to sell-off old asset to eliminate accounting loss from depreciation. An efficiency hypothesis variable is 3-year average (with 2-year forward looking and current) return on assets which $ROA_{avg,t}$.

Under the **Growth and Uncertainty hypothesis**, it is believed that firms' growth protects against disinvestment. Therefore, if firms do not invest to keep up with depreciation or sell-off assets, it is because they lack growth either in the current or future prospect. A growth hypothesis variable is captured by total asset growth ($TAGrowth_{i,t}$). [30] In addition, three-year standard deviation (with 2-year forward looking and current) of return on assets $ROA_{std,t}$ is added here to capture future uncertainty outlook.

5.3.2 Conditional Logistic Regression Results

Table 5 below reports the results from the baseline fixed-effect logit model. Original logit regression coefficients (in terms of log odds) are translated into odds ratio for the convenience of interpretation. To be precise, a one unit change in the right hand side explanatory variables will increase the odds of disinvest (probability of disinvesting over not disinvesting) by a factor equal to the odds-ratio reported below.

[29] See Ding *et al* (2010) for a review of disinvestment hypotheses.

[30] The majority of the firms are of small size and fixed asset (capital) is only about 0-15% of total asset the whole studying period; therefore, we believe $TAGrowth_{i,t}$ is not perfectly correlated with $Disinvestment_{i,t}$

The results are shown separately by size decile in Table 5. Here, we will control for firm (α_i) and time (α_t) fixed effects. [31]

From the **financing hypothesis**, the odds-ratio for these variables do not differ much from 1 across all firm' sizes. This implies that financing constraint variables (net income over capital at the beginning of the period, current asset over capital at the beginning of the period, leverage ratio, and debt flow) do not affect the decision to disinvest. the probability of disinvesting does not differ much across firm' size based on this hypothesis. It is possible that there are other factors beyond financing factors that explain firms' disinvestment behavior. This is in accordance with the conclusion in section 5.2.4.

Considering the **efficiency or restructuring hypothesis**, odds-ratio of $ROA_{avg,t}$ is less than 1 for small firms while it is more than 1 for large firms. Higher three-year average ROA (or higher profitability) will decrease the probability of disinvesting for small firms. Thus, the efficiency hypothesis provides a good explanation for small firms but not for large firms.

The pattern is interesting for the **growth hypothesis** as the odds-ratio of $TAGrowth_{i,t}$ differs significantly from 1 and across firm size. The odds-ratio for small firms are larger than that of large firms, implying that larger firms are more responsive to growth opportunities. If large firms were to have growth opportunity, they would be less likely to make disinvestment decision. Also, **uncertainty** of the growth outlook has more effect in increasing the probability of disinvesting for large firms at decile 9 and decile 10 as the coefficients for the odds-ratios are more than 1 for $ROA_{std,t}$. Thus, the growth and uncertainty hypothesis provides a good explanation for large firms.

[31] Letting the odds ratio be κ.
If $\kappa > 1$, an increase in the explanatory variable will *increase* the probability of disinvesting (versus not disinvesting) by $\kappa - 1$ percent.
If $\kappa = 1$, an increase in the explanatory variable will *leave* the probability of disinvesting (versus not disinvesting) *unaffected*.
If $\kappa < 1$, an increase in the explanatory variable will *decrease* the probability of disinvesting (versus not disinvesting) by $1 - \kappa$ percent.

Variable	decile1	decile2	decile3	decile4	decile5	decile6	decile7	decile8	decile9	decile10
Financing Hypothesis										
NI_t/K_{t-1}	1.000	1.000***	1.000***	1.000	1.000***	0.995***	0.998***	0.995***	1.001	0.997
CA_t/K_{t-1}	1.000***	0.999***	0.998***	0.994***	0.984***	0.981***	0.982***	0.982***	0.969***	0.973***
$Lev_{i,t}$	1.001***	1.005***	1.005***	1.013***	1.024***	1.027***	1.020***	1.008***	1.033***	1.014*
$\Delta D_t/K_{t-1}$	1.000***	1.000	1.000***	1.000	1.000	1.000	1.001***	1.000	1.000	1.000
Efficiency Hypothesis										
$ROA_{avg,t}$	0.952	0.887***	0.829***	0.800***	0.634***	0.857*	0.571***	0.675***	0.785*	1.388***
Growth and Uncertainty Hypothesis										
$ROA_{std,t}$	0.962*	0.983	0.936*	1.029	0.942	1.101	1.114	0.918	1.410***	1.213***
$TAGrowth_{i,t}$	0.994**	0.932***	0.811***	0.719***	0.540***	0.396***	0.288***	0.199***	0.0805***	0.022***
no. of obs	57,504	64,837	64,019	56,061	63,849	72,442	78,800	87,250	97,085	111,470

Table 5: Result (odds-ratio) from conditional logit model by firms' size decile

In conclusion, the logit results here suggest that small firms that are not efficient are more likely to disinvest while large firms disinvest because they lack growth prospect.

• Small firms' decision not to invest more than depreciation rate is more likely to be explained by *efficiency hypothesis*: if small firms are more efficient, they are less likely to disinvest. Put differently, they are more likely to have negative net investment when they are less efficient or to restructure themselves by selling off outdated assets in order to eliminate old capital in the face of more market competitive environment.

• Large firms' decision not to invest more than depreciation rate, however, is more likely to be explained by *growth and uncertainty hypothesis*. Higher growth will significantly decrease large firms' decision to disinvest; therefore, large firms tend to disinvest as they lack growth opportunity. Also, large firms seem to be more susceptible to outlook uncertainties compared to small firms.

Robustness check using firm-level total factor productivity $TFP_{i,t-1}$ as an alternative proxy for the efficiency hypothesis is presented in Table 6. Calculation of firm-level TFP are outlined in Appendix G.

Conclusions from Table 6 are in line with those from Table 5 that small firms' decisions to invest below depreciation rate are sensitive to $TFP_{i,t-1}$ or the efficiency hypothesis while large firms are sensitive to $TAGrowth_{i,t}$ or growth hypothesis.

Variable	decile1	decile2	decile3	decile4	decile5	decile6	decile7	decile8	decile9	decile10
Financing Hypothesis										
NI_t/K_{t-1}	1.000***	0.999***	0.999***	0.998***	0.998***	0.988***	0.991***	0.998	0.977***	0.996
CA_t/K_{t-1}	1.000***	1.000***	0.999***	0.995***	0.987***	0.988***	0.984***	0.985***	0.975***	0.989***
$Lev_{i,t}$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$\Delta D_t/K_{t-1}$	1.000***	1.000***	1.000	1.000***	1.000***	1.000	1.002***	1.000	1.000	1.000
Efficiency Hypothesis										
TFP_{t-1}	0.667***	0.731***	0.804***	0.826***	0.806***	0.854***	0.880***	0.801***	0.875***	0.926***
Growth and Uncertainty Hypothesis										
$ROA_{std,t}$	1.000	1.005	1.033*	1.003	1.000	1.024	1.019	1.002	1.002	1.039*
$TAGrowth_{i,t}$	0.967**	0.932***	0.806***	0.745***	0.537***	0.391***	0.284***	0.204***	0.0813***	0.0255***
no. of obs	22,601	40,660	46,544	41,373	46,699	55,606	61,941	69,726	77,835	93,192

Table 6: Result (odds-ratio) from conditional logit model by firms' size decile

6 Conclusions and Discussion

Using firm-level data of virtually all registered firms in Thailand, this paper argues that the low investment puzzle at the macro level has been partly a result of deep-rooted supply-side problems rather than merely lack of demand.

Simple stylized facts show that more than 60 percent of Thai firms disinvest each year since the post-Asian crisis. Overall, firms that disinvest are found to be less efficient than firms with positive net investment position (investing more than depreciation rate). Nevertheless, within both positive and negative net investment groups, small firms are not necessarily less productive or less efficient than larger firms (small firms on average have higher efficiency ratios: ROA and asset turnover ratio). Small firms, however, have lower leverage ratio compared to larger firms, possibly reflecting more limited access to credit among smaller-sized firms.

The regression analysis based on Tobin's Q model confirms that the level of investment of small firms is constrained by lack of access to external financing. Small firms, however, appear to be making more efficient investments as their investments can be better explained by Tobin's Q than larger firms. The results also confirm that large firms, though less efficient on average, do not have problems accessing to external finance. This finding point to a problem of capital misallocation as more efficient firms do not have enough access to financing, hence, holding back their otherwise productive investments.

Using limited dependent variable model, we find that small firms that are relatively inefficient or less productive compared to their peers (could be due to fierce market competition, lack of market power, or lack of low-cost funding) are more likely to disinvest. In contrary, lack of efficiency does not affect large firms' probability to disinvest, but rather their investment decisions appear to be driven mainly by growth outlook and uncertainties. In other words, large firms are likely to disinvest in the face of weak growth prospects or high future uncertainties.

Taken together, we find that small firms and large firms have been facing different kinds of problems that have ultimately led to persistently low investment observed in the Thai economy since the Asian crisis. Small firms, which are the majority of Thai firms, face more of the supply-side problems. Some of the small firms are not productive or efficient enough so that they have to undergo a period of disinvestment, either to restructure their operation or before they leave the market altogether. Other small firms that are relatively more efficient are constrained by lack of external financing that holds them back from investing more. On the other hand, the demand-side problem could be at work to some extent for large firms which are typically do not have problems accessing to finance.

These findings have important implications for current policy debates. For instance, efficient small firms which have higher potential and incentive to invest need support from the credit access policy, while the less efficient small firms need supports in terms of knowledge and management skill enhancement or product innovation to help improve their efficiency and get them through increasing market competition. The results also imply that some existing policies that focus on relaxing demand-side constraints, such as tax incentive policy, may not be sufficient as they may not be the right solution for all types of firms that face different investment obstacles.

This paper highlights the importance of using more micro-level data to really understand the underlying factors that give rise to broader, macro-level phenomena. However, caveats and some data limitations do exist. In constructing the proxy for (unobservable) marginal Q variable, we assume perfect competition. This is subjected to discussions among past literatures and could possibly bias the result. [32]

Also, there are other related issues that have not been explored in this paper; for example, labor quality or labor shortage problems, or market competition structure, that may be other plausible explanations for low investment in Thailand. Nor are we able to explain the underlying reasons for each of our findings (i.e. why small firms, even the efficient ones, do not have sufficient access to external financing). Future research in this area is needed to fully understand the big picture in order

[32] To be precise, if the market were imperfect, some firms earn rents and are capitalized in their valuation, our Q may not be a perfect predictors of investment and there may arise measurement error. See Hayashi (1982) for a discussion.

to design appropriate policy responses targeted at each type of problem.

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A Appendix: Sectoral Net Investment

Sectoral net investment here is constructed from growth of "sector-aggregated" private fixed capital stock each year. Therefore, we are still unable to uncover variations at the firm-level, e.g. how many firms have negative net investment each year, which types of firms are having negative net investment, and it is worth exploring further more in-depth through the firm-level dataset.

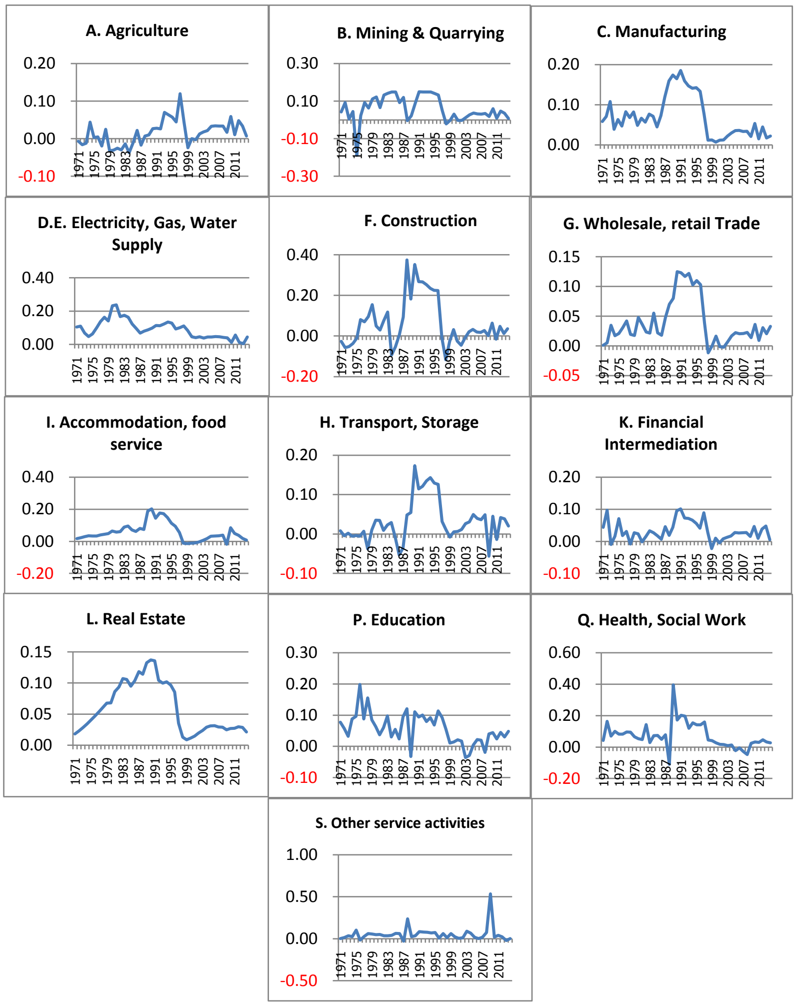

Figure 18: Macro-level Net Investment (year-on-year growth of sector-aggregated private capital stock). Source: NESDB annual sectoral capital stock data (1971-2014).

B Appendix: Structural VAR with Sign restriction

B.1 model

The present section describes the baseline empirical model, bivariate structural vector autoregression (SVAR), identified by sign restrictions. Let $x_t \equiv [\ \Delta i_t,\ \Delta y_t\ ]$, i_t is log of private gross fixed capital formation (investment), y_t is log of real GDP. The focus on these two variables are motivated by its central role in studying investment share in output. I assume the joint process follows the following VAR representations:

$$x_t = A_1 x_{t-1} + A_2 x_{t-2} + ... + A_p x_{t-p} + u_t \tag{5}$$

A_0 is the vector of constant and A_i where i = 1,2,..p are matrices of coefficients. u_t is the reduced form white noise error. Lag length is determined by the standard likelihood ration tests and Akaike's criterion (AIC), which turns out to be one. Noted here that AR(1) can be rewritten in the MA(q) representation where q = ∞. Letting output and investment growth follows the bivariate process explained solely be external shocks is in line with the intuition of several existing theoretical studies.[33] The structural VAR map the reduced form forecast errors (u_t) into structural shocks (ϵ_t) by

$$u_t = B\epsilon_t \tag{6}$$

ϵ_t is the orthogonal shock with economic meaning and E$(\epsilon_t \epsilon_t') = I$. Sign restrictions used to identify matrix B will be discussed in the next section.[34]

B.2 identification discussion

By examining the correlation between the growth of investment and output, we separate the types of shocks relevant to identify the VAR model into two groups according to the Neoclassical theory of investment: shocks to aggregate production function that increase the correlation between the cyclicality of investment and output, shocks to the marginal productivity of capital that decrease the correlation between the cyclicality of investment and output. Thus, we assume there are only two sources of structural shocks that can affect the cyclicality of investment and output in the *long run*.

The first type of shock (ϵ_1), shock to marginal productivity of capital or the relative cost of capital, which may affect the level of investment and output in the opposite directions, thus reduce the correlation among investment and output.

[33] See Shapiro (1986) for theoretical derivation from the general equilibrium model for similar joint process relationship.

[34] SVAR with sign restriction method is similar to Rubio-Ramirez *et al.* (2010); Benes, Johnston, and Plotnikov (2014).

The second type (ϵ_2), shock to aggregate production function, which will affect the level of investment and output in the same direction, thus increase the correlation among the two variables.

All sign restrictions that will be used to identify MPK and aggregate production function innovations are summarized in Table 7.

Variable	**shock 1**	**shock 2**
i_t	+	+
y_t	-	+

Table 7: sign restrictions

Technical construction is as follows: (1) Randomly factorize var-cov matrix of the reduced form residual ($\Sigma = \mathrm{E}(u_t u_t')$) (2) Draw matrix X from N(0,1) (3) Compute the QR decomposition of X (4) Normalize the diagonal of R to be positive, compute the impulse response of that SVAR, check if the sign restrictions are satisfied. (5) Repeat step 1-4 until 500 success draws are obtained.

To answer the question which types of shock has affected the economy during the whole considered period, I estimate the VAR system (equation 6) with the sign restriction discussed in the previous section on a rolling window of 20 quarters each. The estimation is based on Thai NESDB quarterly data from 1993Q1-2015Q1. The impulse response function is calculated and the variance decomposition statistics are sorted from 500 success impulse response which is the closest to the median. The result is presented in Figure 3 of section 3.2

C Appendix: Financial Ratio Formula

asset turnover ratio	= sales/total asset
operating profit margin	= net income before interest and tax/sales
	= (revenue - expense)/sales
	= (revenue - cost of goods sold - SG&A)/sales
	SG&A is selling, general, and administrative expenses
gross profit margin	= (revenue - cost of goods sold)/sales
return on asset, ROA	= net income before interest and tax/total asset
	= operating profit margin* asset turnover ratio
leverage ratio	= total debt/total asset
current ratio	= current asset/current liabilities

D Appendix: CPFS Firm-Level Data Description

D.1 Description of each Industry

A.	Agricultural,forestry,fishing	J.	Information, communication
B.	Mining, quarrying	K.	Financial, insurance activities
C.	Manufacturing	L.	Real estate
D.	Electricity, gas, steam	M.	Professional, scientific and technical activities
E.	Water supply	N.	Administrative, support activities
F.	Construction	P.	Education
G.	Wholesale, retail trade	Q.	Human health, social work activities
H.	Transport, storage	R.	Arts, entertainment, recreation
I.	Accommodation, food service	S.	Other service activities

D.2 Distribution Plot

This section provides the density plot of major panel data regression variables: net investment over initial capital (or fixed capital growth), current assets over initial capital, net income over initial capital, average 3-year return on asset, leverage ratio, and debt flow. The sample are separated into full sample, positive net investment and negative net investment.

D.3 Appendix: Full Sample

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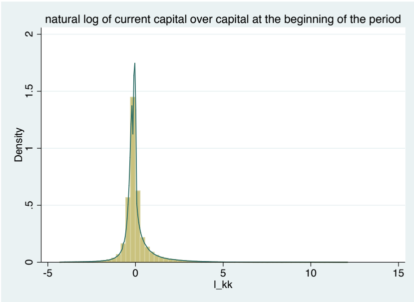

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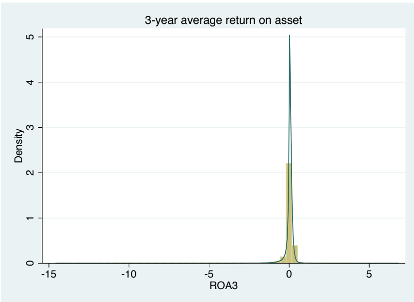

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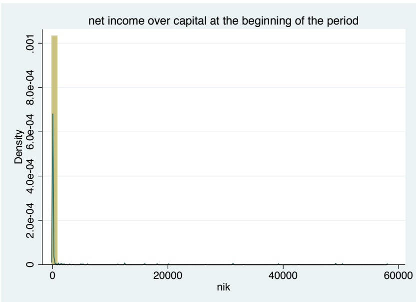

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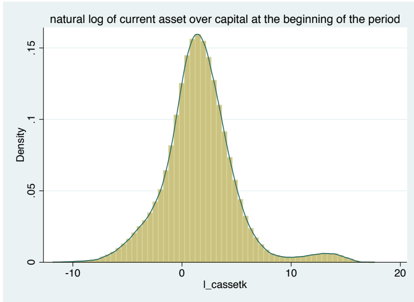

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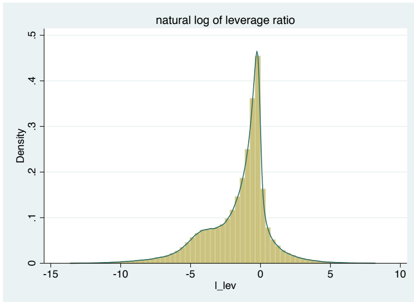

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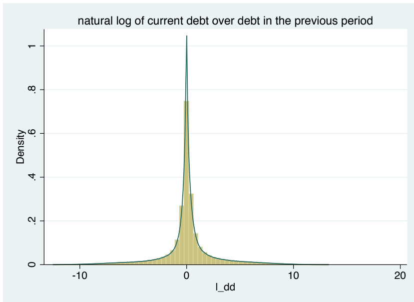
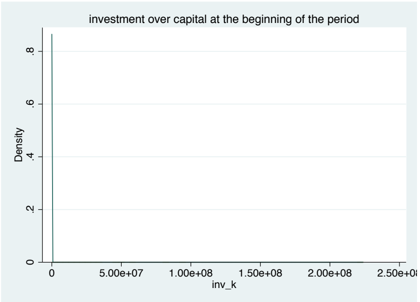


D.4 Appendix: Positive Investment Sample



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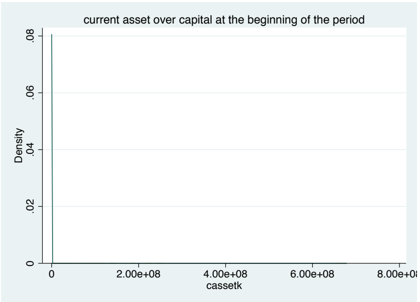

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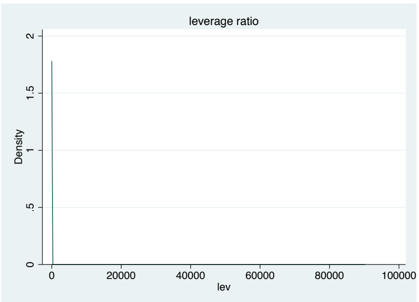

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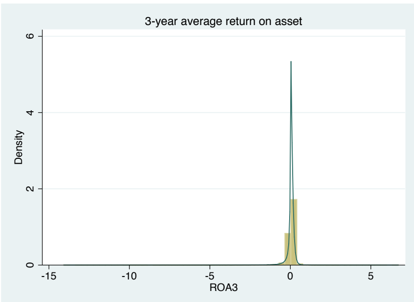

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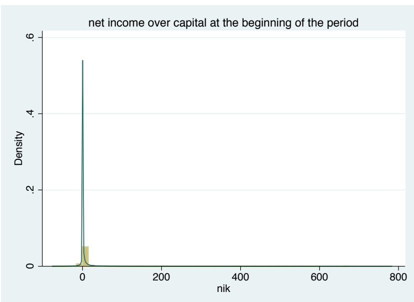

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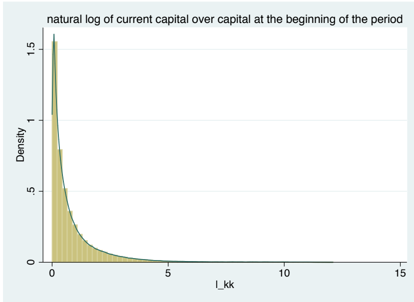

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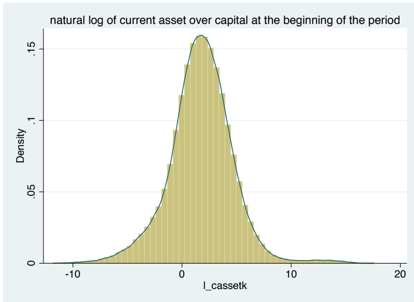

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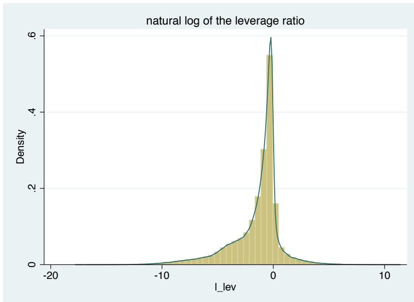

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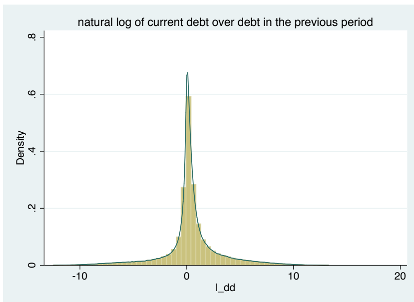

9.

D.5 Appendix: Negative Investment Sample

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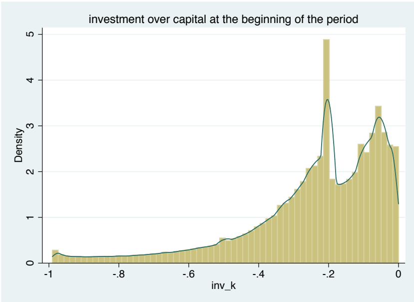

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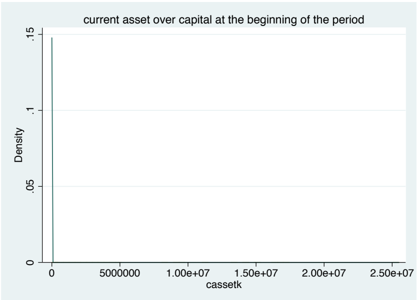

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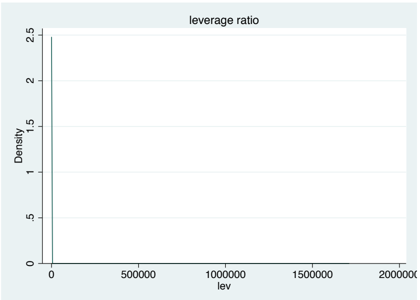

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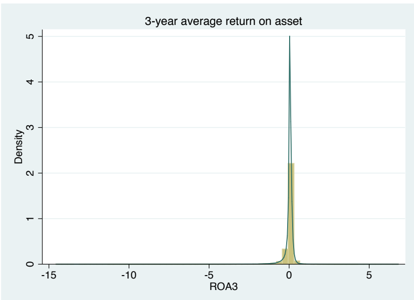

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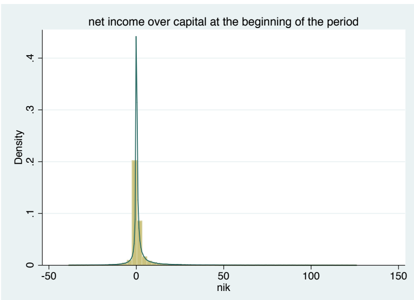

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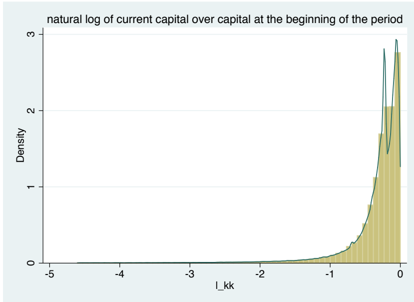

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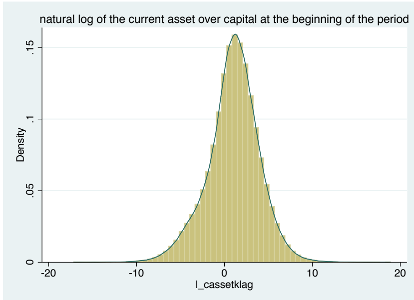

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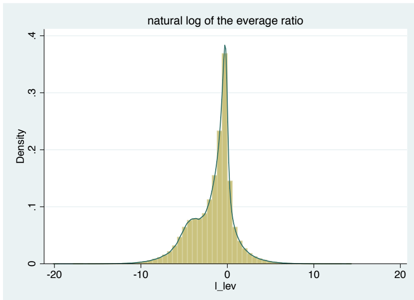

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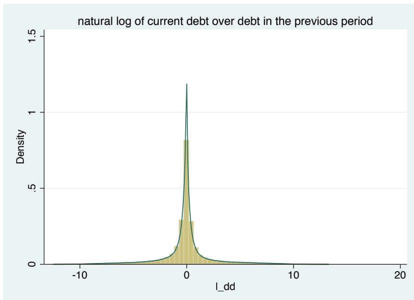

E Appendix: Regression with size decile interaction effect

Variable	Positive net investment				Negative net investment	
	(1)	(2)	(3)	(4)	(1)	(2)
$ROA_{avg,t}$	0.074**	0.103**	0.034*	0.089**	0.016**	0.017**
$\ln(CA_{t-1}/K_{t-1})$	0.377**	0.424**		0.363**	0.041**	0.046**
NI_{t-1}/K_{t-1}			0.000**	0.000**		
$\ln(lev_{t-1})$		0.106**		0.090**		-0.002
$\ln(D_t/D_{t-1})$		0.040**		0.037**		0.013**
$I_{decile2} * ROA_{avg,t}$	-0.034	-0.025	-0.013	-0.009	-0.010**	-0.011**
$I_{decile2} * \ln(CA_{t-1}/K_{t-1})$	-0.107**	-0.103**		-0.071**	0.028**	0.032**
NI_{t-1}/K_{t-1}			0.000**	0.000**		
$I_{decile2} * \ln(lev_{t-1})$		-0.031**		-0.022**		0.006**
$I_{decile2} * \ln(D_t/D_{t-1})$		0.000		0.002		0.003†
$I_{decile3} * ROA_{avg,t}$	0.017	0.016	0.038	0.025	-0.004	-0.005†
$I_{decile3} * \ln(CA_{t-1}/K_{t-1})$	-0.065**	-0.059**		-0.015†	0.010**	0.013**
NI_{t-1}/K_{t-1}			0.000	0.000*		
$I_{decile3} * \ln(lev_{t-1})$		-0.034**		-0.024**		0.009**
$I_{decile3} * \ln(D_t/D_{t-1})$		0.016**		0.020**		-0.003*
$I_{decile4} * ROA_{avg,t}$	0.024	0.03 7	0.065†	0.046	-0.009**	-0.010**
$I_{decile4} * \ln(CA_{t-1}/K_{t-1})$	-0.049**	-0.035**		0.012	-0.007**	-0.005*
NI_{t-1}/K_{t-1}			0.000†	0.000*		
$I_{decile4} * \ln(lev_{t-1})$		-0.012†		-0.001		0.010**
$I_{decile4} * \ln(D_t/D_{t-1})$		0.022**		0.025**		-0.006**
$I_{decile5} * ROA_{avg,t}$	0.016	0.002	0.046	0.013	-0.008*	-0.009*
$I_{decile5} * \ln(CA_{t-1}/K_{t-1})$	-0.081**	-0.062**		-0.006	-0.014**	-0.013**
NI_{t-1}/K_{t-1}			0.000†	0.000†		
$I_{decile5} * \ln(lev_{t-1})$		-0.007		0.007		0.008**
$I_{decile5} * \ln(D_t/D_{t-1})$		0.012**		0.016**		-0.007**
$I_{decile6} * ROA_{avg,t}$	-0.056*	-0.074**	0.001	-0.062*	-0.014**	-0.014**
$I_{decile6} * \ln(CA_{t-1}/K_{t-1})$	-0.115**	-0.100**		-0.043**	-0.021**	-0.022**
NI_{t-1}/K_{t-1}			0.000	0.000		
$I_{decile6} * \ln(lev_{t-1})$		-0.018**		-0.004		0.007**
$I_{decile6} * \ln(D_t/D_{t-1})$		0.007†		0.010*		-0.009**
$I_{decile7} * ROA_{avg,t}$	-0.099*	-0.113*	-0.092†	-0.106*	-0.018**	-0.018**
$I_{decile7} * \ln(CA_{t-1}/K_{t-1})$	-0.141**	-0.126**		-0.067**	-0.024**	-0.026**
NI_{t-1}/K_{t-1}			0.000**	0.000**		
$I_{decile7} * \ln(lev_{t-1})$		-0.021**		-0.007		0.005*
$I_{decile7} * \ln(D_t/D_{t-1})$		0.006		0.009†		-0.009**
$I_{decile8} * ROA_{avg,t}$	-0.049	-0.089*	0.040	-0.076†	-0.020**	-0.020**
$I_{decile8} * \ln(CA_{t-1}/K_{t-1})$	-0.163**	-0.151**		-0.090**	-0.028**	-0.032**
NI_{t-1}/K_{t-1}			0.000	0.000		
$I_{decile8} * \ln(lev_{t-1})$		-0.036**		-0.021**		-0.001**
$I_{decile8} * \ln(D_t/D_{t-1})$		0.013**		0.016**		-0.009**
$I_{decile9} * ROA_{avg,t}$	-0.118**	-0.157**	-0.019	-0.143**	-0.025**	-0.025**
$I_{decile9} * \ln(CA_{t-1}/K_{t-1})$	-0.181**	-0.176**		-0.115**	-0.031**	-0.037**
NI_{t-1}/K_{t-1}			0.000	0.000		
$I_{decile9} * \ln(lev_{t-1})$		-0.055**		-0.040**		-0.004*
$I_{decile9} * \ln(D_t/D_{t-1})$		0.011**		0.014**		-0.007**
$I_{decile10} * ROA_{avg,t}$	-0.360**	-0.382**	-0.351**	-0.366**	-0.017**	-0.017**
$I_{decile10} * \ln(CA_{t-1}/K_{t-1})$	-0.218**	-0.199**		-0.138**	-0.033**	-0.041**
NI_{t-1}/K_{t-1}			-0.001†	-0.001†		
$I_{decile10} * \ln(lev_{t-1})$		-0.037**		-0.022**		-0.006**
$I_{decile10} * \ln(D_t/D_{t-1})$		-0.003		0.001		-0.007**
no. of observation	445,514	445,514	445,514	445,514	1,000,387	1,000,387

F Appendix: Regression Results for Positive Net Investment Sample

F.1 Regression with industry dummy

Variable	Coefficient	Variable	Coefficient
$ROA_{avg,t}$	0.095**	$I_J * ROA_{avg,t}$	0.080†
$\ln(CA_{t-1}/K_{t-1})$	0.200**	I_J * $\ln(CA_{t-1}/K_{t-1})$	0.131**
$\ln(lev_{t-1})$	0.051**	I_J *$\ln(lev_{t-1})$	-0.002
$\ln(debt_t/debt_{t-1})$	0.033**	I_J *$\ln(debt_t/debt_{t-1})$	0.045**
$I_B * ROA_{avg,t}$	-0.131	$I_K * ROA_{avg,t}$	0.058
I_B * $\ln(CA_{t-1}/K_{t-1})$	0.141**	I_K * $\ln(CA_{t-1}/K_{t-1})$	0.104**
I_B *$\ln(lev_{t-1})$	0.007	I_K *$\ln(lev_{t-1})$	0.056*
I_B *$\ln(debt_t/debt_{t-1})$	0.012	I_K *$\ln(debt_t/debt_{t-1})$	-0.005
$I_C * ROA_{avg,t}$	-0.073*	$I_L * ROA_{avg,t}$	-0.036
I_C * $\ln(CA_{t-1}/K_{t-1})$	0.066**	I_L * $\ln(CA_{t-1}/K_{t-1})$	0.090**
I_C *$\ln(lev_{t-1})$	0.034†	I_L *$\ln(lev_{t-1})$	0.003
I_C *$\ln(debt_t/debt_{t-1})$	0.000	I_L *$\ln(debt_t/debt_{t-1})$	0.025*
$I_D * ROA_{avg,t}$	-0.179**	$I_M * ROA_{avg,t}$	0.010
I_D * $\ln(CA_{t-1}/K_{t-1})$	0.209**	I_M * $\ln(CA_{t-1}/K_{t-1})$	0.134**
I_D *$\ln(lev_{t-1})$	-0.011	I_M *$\ln(lev_{t-1})$	0.030
I_D *$\ln(debt_t/debt_{t-1})$	0.125*	I_M *$\ln(debt_t/debt_{t-1})$	0.018
$I_E * ROA_{avg,t}5$	-0.146	$I_N * ROA_{avg,t}14$	0.047
I_E * $\ln(CA_{t-1}/K_{t-1})$	0.149**	I_N * $\ln(CA_{t-1}/K_{t-1})$	0.122**)
I_E *$\ln(lev_{t-1})$	0.096*	I_N *$\ln(lev_{t-1})$	0.029
I_E *$\ln(debt_t/debt_{t-1})$	-0.013	I_N *$\ln(debt_t/debt_{t-1})$	0.010
$I_F * ROA_{avg,t}$	0.225**	$I_P * ROA_{avg,t}$	0.020
I_F * $\ln(CA_{t-1}/K_{t-1})$	0.172**	I_P * $\ln(CA_{t-1}/K_{t-1})$	0.125**
I_F *$\ln(lev_{t-1})$	0.037†	I_P *$\ln(lev_{t-1})$	-0.037
I_F *$\ln(debt_t/debt_{t-1})$	0.026*	I_P *$\ln(debt_t/debt_{t-1})$	0.037†
$I_G * ROA_{avg,t}$	-0.030	$I_Q * ROA_{avg,t}$	0.064
I_G * $\ln(CA_{t-1}/K_{t-1})$	0.152**	I_Q * $\ln(CA_{t-1}/K_{t-1})$	0.045
I_G *$\ln(lev_{t-1})$	0.063**	I_Q *$\ln(lev_{t-1})$	0.019
I_G *$\ln(debt_t/debt_{t-1})$	0.006	I_Q *$\ln(debt_t/debt_{t-1})$16	0.008
$I_H * ROA_{avg,t}$	-0.102†	$I_R * ROA_{avg,t}17$	-0.119
I_H * $\ln(CA_{t-1}/K_{t-1})$	0.131**	I_R * $\ln(CA_{t-1}/K_{t-1})$	0.113**
I_H *$\ln(lev_{t-1})$ 8	0.025	I_R *$\ln(lev_{t-1})$	0.004
I_H *$\ln(debt_t/debt_{t-1})$	0.025*	I_R *$\ln(debt_t/debt_{t-1})$	0.024
$I_I * ROA_{avg,t}$	-0.069*	$I_S * ROA_{avg,t}$	-0.044
I_I * $\ln(CA_{t-1}/K_{t-1})$	0.064**	I_S * $\ln(CA_{t-1}/K_{t-1})$	0.111**
I_I *$\ln(lev_{t-1})$	-0.016	I_S *$\ln(lev_{t-1})$	0.015
I_I *$\ln(debt_t/debt_{t-1})$	0.022†	I_S *$\ln(debt_t/debt_{t-1})$	0.018

Table 8: number of observation(invested firms) = 445,514

F.2 Regression by industry with size quartile interaction effect

	Indus A	Indus B	Indus C	Indus D	Indus E	Indus F
$ROA_{avg,t}$	-0.757	0.261	0.000281	-6.546***	-0.868	0.255***
$\ln(CA_{t-1}/K_{t-1})$	0.369**	0.499***	0.311***	-0.450**	0.492**	0.370***
$\ln(lev_{t-1})$	0.115	0.130	0.0908***	0.856***	0.171	0.0570***
$\ln(debt_t/debt_{t-1})$	0.0300	0.0647	0.0230***	-0.329	-0.00269	0.0532***
$I_{quartile2} * ROA_{avg,t}$	0.284	0.584	0.179**	6.446***	1.047	0.258**
$I_{quartile2} * \ln(CA_{t-1}/K_{t-1})$	-0.151	-0.00386	0.0187	0.485*	-0.0958	0.0209
$I_{quartile2} * \ln(lev_{t-1})$	-0.0708	0.0153	-0.0196	-0.688*	0.0284	0.0280
$I_{quartile2} * \ln(debt_t/debt_{t-1})$	-0.0505	0.0396	0.0335***	0.887*	-0.0197	0.0174
$I_{quartile3} * ROA_{avg,t}$	1.018	0.340	-0.00536	12.13***	-0.461	0.113
$I_{quartile3} * \ln(CA_{t-1}/K_{t-1})$	-0.205	-0.219	-0.0693***	0.954***	-0.152	-0.0203
$I_{quartile3} * \ln(lev_{t-1})$	-0.102	-0.0870	-0.0332**	-1.327***	-0.0920	0.0420**
$I_{quartile3} * \ln(debt_t/debt_{t-1})$	0.0152	-0.0651	0.0153*	0.565*	0.0976	-0.00418
$I_{quartile4} * ROA_{avg,t}$	0.379	-0.0646	-0.449***	5.746***	-0.216	0.262
$I_{quartile4} * \ln(CA_{t-1}/K_{t-1})$	-0.235	-0.262*	-0.141***	0.966***	-0.209	-0.106***
$I_{quartile4} * \ln(lev_{t-1})$	-0.0848	-0.110	-0.0497***	-0.854***	-0.0663	0.00990
$I_{quartile4} * \ln(debt_t/debt_{t-1})$	0.00790	-0.0119	0.0117	0.504**	0.0131	-0.00472
$I_{quartile2}$	2.004***	1.292*	0.865***	0.365	1.110	0.875***
$I_{quartile3}$	2.404***	2.158***	1.360***	2.242*	2.113**	1.257***
$I_{quartile4}$	2.747***	2.438***	1.696***	2.589**	2.717***	1.712***
constant	-1.589**	-1.076	-0.587***	0.376	-0.478	-0.327***
no. of observation	2,468	1,784	97,835	474	742	37,277

	Indus G	Indus H	Indus I	Indus J	Indus K	Indus L
$ROA_{avg,t}$	0.0540	-0.0412	0.0159	0.166**	0.203**	0.0935*
$\ln(CA_{t-1}/K_{t-1})$	0.343***	0.327***	0.257***	0.286***	0.340***	0.304***
$\ln(lev_{t-1})$	0.0928***	0.0709***	0.0400*	0.0257	0.0922***	0.0910**
$\ln(debt_t/debt_{t-1})$	0.0301***	0.0484***	0.0241	0.0562***	0.0347	0.0617*
$I_{quartile2} * ROA_{avg,t}$	0.0546	0.330	-0.00650	-0.0262	0.350	-0.0163
$I_{quartile2} * \ln(CA_{t-1}/K_{t-1})$	0.0407***	0.0303	0.00840	0.0414	0.0481	0.0551
$I_{quartile2} * \ln(lev_{t-1})$	0.0240***	0.0103	-0.00895	-0.0380	0.0456	-0.00127
$I_{quartile2} * \ln(debt_t/debt_{t-1})$	0.0175***	0.00404	0.0284	0.0776***	0.0172	0.0209
$I_{quartile3} * ROA_{avg,t}$	-0.0578	0.234	-0.260*	-0.0125	-0.254	-0.0561
$I_{quartile3} * \ln(CA_{t-1}/K_{t-1})$	-0.0345***	0.0289	-0.00827	0.00175	-0.0861*	-0.0468
$I_{quartile3} * \ln(lev_{t-1})$	0.0127	0.0214	-0.0595*	0.0192	-0.0143	-0.00680
$I_{quartile3} * \ln(debt_t/debt_{t-1})$	0.00551	0.0196	0.0646***	0.00204	-0.00301	-0.0251
$I_{quartile4} * ROA_{avg,t}$	-0.230*	0.00916	-0.0462	0.174	-0.437***	0.0441
$I_{quartile4} * \ln(CA_{t-1}/K_{t-1})$	-0.0530***	-0.0874**	-0.0249	-0.0265	-0.173***	-0.0260
$I_{quartile4} * \ln(lev_{t-1})$	0.00978	-0.0344	-0.00780	0.0701	-0.0355	-0.0595
$I_{quartile4} * \ln(debt_t/debt_{t-1})$	0.0118*	0.0150	0.0325	-0.00769	-0.0165	-0.0118
$I_{quartile2}$	0.881***	0.942***	0.828***	0.510***	0.725***	0.845***
$I_{quartile3}$	1.397***	1.335***	1.478***	0.880***	1.654***	1.701***
$I_{quartile4}$	1.818***	1.734***	1.783***	1.136***	2.243***	2.462***
constant	-0.563***	-0.197*	-0.0563	0.222*	-0.810***	-0.588***
no. of observation	169,454	19,165	17,348	9,769	5,756	17,969

	Indus M	Indus N	Indus P	Indus Q	Indus R	Indus S
$ROA_{avg,t}$	0.0799	0.140**	0.344	0.0461	0.110	0.0139
$\ln(CA_{t-1}/K_{t-1})$	0.315***	0.291***	0.290***	0.146	0.360***	0.247***
$\ln(lev_{t-1})$	0.0803***	0.0551***	-0.0468	0.0409	0.120**	0.0755*
$\ln(debt_t/debt_{t-1})$	0.0344***	0.0334***	0.0647*	-0.0175	0.00331	-0.00234
$I_{quartile2} * ROA_{avg,t}$	0.210**	0.0678	-0.254	0.0388	0.104	-0.00234
$I_{quartile2}$ * $\ln(CA_{t-1}/K_{t-1})$	0.00403	0.0606*	0.0611	0.166	-0.0345	0.0770
$I_{quartile2}$ * $\ln(lev_{t-1})$	-0.0269*	0.0140	-0.0533	0.0543	-0.135**	-0.0445
$I_{quartile2}$ * $\ln(debt_t/debt_{t-1})$	0.0298**	0.0267*	0.0449	0.0557	0.105**	0.0763*
$I_{quartile3} * ROA_{avg,t}$	-0.0396	-0.139*	-0.466	0.292	-0.300**	-0.296
$I_{quartile3}$ * $\ln(CA_{t-1}/K_{t-1})$	-0.0453*	-0.00982	0.0186	0.114	-0.0563	-0.00487
$I_{quartile3}$ * $\ln(lev_{t-1})$	-0.0192	0.00978	0.101	0.0331	-0.0667	-0.0446
$I_{quartile3}$ * $\ln(debt_t/debt_{t-1})$	0.0237*	0.0228	0.0102	0.0776	0.0438	0.0569
$I_{quartile4} * ROA_{avg,t}$	-0.307	0.0941	-0.311	-0.423	-0.387	0.626
$I_{quartile4}$ * $\ln(CA_{t-1}/K_{t-1})$	-0.0398	-0.0341	-0.00965	0.00826	-0.121	-0.0620
$I_{quartile4}$ * $\ln(lev_{t-1})$	0.0164	0.0270	0.135*	-0.0187	-0.0877	-0.0135
$I_{quartile4}$ * $\ln(debt_t/debt_{t-1})$	0.0111	0.0000906	-0.0449	0.0687	0.0604	0.0697*
$I_{quartile2}$	0.816***	0.766***	0.712***	0.420	0.959***	0.622***
$I_{quartile3}$	1.241***	1.192***	1.028***	0.819*	1.465***	0.914***
$I_{quartile4}$	1.519***	1.445***	1.321***	0.891*	1.615***	0.908***
constant	-0.0603	-0.0595	0.305	0.361	-0.187	0.477**
no. of observation	32,851	23,226	2,015	2,290	2,339	2,716

G Appendix: Model and proposed method for combining two datasets, CPFS and LFS

In this section, we lay out the model behind the estimation of the *marginal revenue product of capital* in section 5.1 and propose a method to combine two big data sources: Labour Force Survey (LFS) data and Corporate Profile Financial Statement (CPFS) data. The aim of data combining is to test the efficiency hypothesis of negative net investment in section 5.3. We hope it will be beneficial for future research that wants to study Thailand's firm-level labor data in other aspects. However, they are rife with assumptions that should be carefully taken care of before using.

The Labour Force Survey (LFS) data, the biggest and the only labor data of Thailand containing labor and wages of all Thai workers we need for productivity TFP calculation. However, the data is available only in workers' characteristic level of which can be combined only upto city-ISIC level, not in the firm-level we expect. Moreover it is available only in monthly format. Collapsing them into yearly data and combining them with the Business Online firm-level data set is my best attempt for now. Several assumptions and modifications are made here.

G.1 Production and Demand

We assume firm i produce $Q_{i,t}$ units of goods i. The production function is of the constant return to scale Cobb-Douglas form:

$$Q_{i,t} = A_{i,t} K_{i,t}^{\alpha_i} L_{i,t}^{\beta_i} \tag{7}$$

Firm produce under the downward sloping demand curve,

$$Q_{i,t} = X_{i,t} P_{i,t}^{\frac{-1}{\eta_i}} \tag{8}$$

where η_i is the inverse of firm-specific productivity. For notational convenience, I define $Y_{i,t} \equiv P_{i,t} Q_{i,t}$ as sales revenue. Combining (7) and (8), we get

$$Y_{i,t} = X_{i,t}^{\eta_i} A_{i,t}^{1-\eta_i} (K_{i,t}^{\alpha_i} L_{i,t}^{\beta_i})^{1-\eta_i} \tag{9}$$

For a given productive level of capital stock, a firm choose $L_{i,t}$ to maximize operating profits, $\pi_{i,t}$.

$$\pi_{i,t} = max_{L_{i,t}} \{Y_{i,t} - w_{i,t} L_{i,t}\} \tag{10}$$

First-order condition implies:

$$\frac{w_{i,t} L_{i,t}}{Y_{i,t}} = \beta_i (1 - \eta_i) \tag{11}$$

$$\frac{\pi_{i,t}}{Y_{i,t}} = \eta_i + \alpha_{i,t} (1 - \eta_i) \tag{12}$$

In this paper, we assume perfect elasticity of demand function ($\eta_i = 0$). Accordingly, gross profit over sales revenue will become α_i as profits are just capital income. Arranging (10), (11) and (12) we get,

$$log \pi_{i,t} = log \alpha_i + log A_{i,t} + \alpha_i log K_{i,t} + \beta_i log L_{i,t} \tag{13}$$

$$w_{i,t} L_{i,t} = \beta_i Y_{i,t} \tag{14}$$

$$\frac{\pi_{i,t}}{Y_{i,t}} = \alpha_{i,t} \tag{15}$$

We derive the marginal revenue product of capital used in section 5.1 as:

$$MRPK_{i,t} = \frac{\partial Y_{i,t}}{\partial K_{i,t}} = \alpha_i (1 - \eta_i) \frac{Y_{i,t}}{K_{i,t}} = \frac{\pi_{i,t}}{K_{i,t}} \tag{16}$$

The second equality is from the assumption of perfect demand elasticity (η=0) and substituting in equation (15). The above definition of marginal revenue product of capital equal to operating profit over capital at the beginning period is the central definition used for capital misallocation calculation in Section 5.1. We intentionally used the above maximizing methodology as a representation for capital misallocation estimation so as it will not be subjected to the criticism that the trend in capital misallocation is driven by the trend in technological advancements.

To obtain the firm-level TFP used as a robustness check in section 5.3.2, we further do the following derivation:

Aggregating (14) across city and 4 digit ISIC industry we get,

$$\beta_{in,t} = \frac{\sum_{i \in in, j \in city} w_{i,j,t} L_{i,j,t}}{\sum_{i \in in, j \in city} Y_{i,j,t}} \equiv \beta_{i,t} \tag{17}$$

Note that *in* is the 4-digit ISIC industry in each time period and *city* here represent Thailand's 76 "changwad" or city. The second equality is from the assumption that labor technology is constant within each city and industry, $\beta_{i,j,t} = \beta_{i,t}$. [35]

From here, sum of the wage bill data (nominator) from the LFS dataset is merge with sum of the sales revenue (denominator) from the CPFS data set to get the $\beta_{in,j,t}$

Next, I assume that wages per person is also constant within city and industry, $w_{in,j,t} = w_{i,t}$ and dividing both sides of (14) by $w_{in,j,t}$ we get,

$$L_{i,t} = \frac{\beta_{i,t} Y_{i,t}}{w_{in,j,t}} \tag{18}$$

Equation (18) provide an estimate of the firm-level labor data which can be used for testing efficiency hypothesis of disinvestment. Note here that we use ISIC-rev3 from 2001-2010 and ISIC-rev4 from 2011 to 2012 since it is the only format LFS data provide.[36]

G.2 Summarized steps in obtaining firm level TFP

Step 1: Calculating $\beta_{in,t}$ according to equation 17. where the nominator wage bill is obtained from the monthly Labor Force Survey (LFS) data and the denominator sales is obtained from the Business online data.

Step 2: Merge LFS yearly wage data to CPFS data by 4 digit ISIC industry and year.

Step 3: Calculate firm level labor according to equation 18.

Step 4: Calculate firm level TFP according to equation 13.

[35] Another possible method to obtain $\beta_{i,t}$ is to assume constant return to scale ($\beta_{i,t} = 1 - \alpha_{i,t}$)

[36] ISIC-rev 4 is revised version of ISIC-rev 3 which is more detailed and contained more digit in categorized the data