To make the distinction between these concepts concrete, the reallocation experiment in Hsieh and Klenow (2009) takes countries (the U.S., China, and India) as aggregation units and four-digit ISIC sectors as interchangeability units.

We can then define aggregate output and the aggregate factor stocks over the observed factor utilizations as

Definition 3 (Aggregate Variables) *Define* ***aggregate output in*** I_t *as*

$$Y_{I_t} = \int_{i \in I_t} y_{it}\, di$$

Define the ***aggregate stock of*** k ***in*** $I_{k,m_k t}$ *for any factor* k *as*

$$X_{k,I_{k,m_k t}} = \int_{i \in I_{k,m_k t}} X_{k,it}\, di$$

and the ***aggregate stock of*** k ***in*** I_t *as*

$$\begin{aligned} X_{k,I_t} &= \int_{i \in I_t} X_{k,it}\, di \\ &= \sum_{m_k} X_{k,I_{k,m_k t}} \end{aligned}$$

Note that this definition of aggregate output differs from that of some other work in the literature, e.g. Hsieh and Klenow (2009); Alfaro et al. (2008); Bartelsman et al. (2009), where Y_{I_t} is defined as a CES aggregate of some sort. I choose a simple additive definition because it more closely mirrors actual GDP accounting and yields the convenient properties to be highlighted in Proposition 3 below.

2.2. Defining Factor Allocative Efficiency

The intuitive concept of factor allocative efficiency is a comparison of output observed as compared to some counterfactual benchmark where the aggregate stock of resources is identical but firm-level allocations of those factors achieve greater aggregate output. The following definition formalizes the intuition behind this notion:

owned assets is then aggregated yearly for each household and combined with the value of rented assets. One concern with this approach is that capital useful for rice production (e.g. tractors, crop-storage structures) may also be used for growing other crops (e.g. maize), and thus reallocation based solely on observation of rice outcomes would fail to account for the capital's other uses. To check whether this affects the results, I define a separate sample of households that farm only rice in a given year and recompute all results on that sample in addition to the more expansive sample (see Section 5.).

Control variables that help comprise the dynamic elements of TFP are also defined using the household survey. For more details, see Appendix A.

4.3. Descriptive Statistics

Panel A of Figure I plots several descriptive statistics related to the rice farmers in the sample, where an individual is defined to be farming rice if they report both positive revenues from rice and positive use of all three factors. Immediately apparent is that agriculture in Thailand is far more non-traditional and commercialized than most developing countries even at baseline, and it becomes increasingly so throughout the sample period. Almost all farmers report using modern farming techniques (fertilizers or pesticides). At baseline, slightly more than half of farmers rent capital (implying the existence of functioning rental markets), and this fraction rises to nearly 80% by 2008. And although only about 30% are hiring labor at baseline, this fraction has increased more than 2.5-fold by the end of the sample. The fraction renting land shows no particular trend but is well above 20% throughout the sample. Despite this evidence of functioning factor markets, every single rice farmer in the dataset reports receiving free labor (either through reciprocal trades or other arrangements) and borrowing capital from friends and relatives. Perhaps the most dramatic stylized fact, however, is that from 1996 to 2008, the fraction of rice farmers reporting financing constraints or any other factor hiring constraint in profitable expansion declines from roughly half to almost zero.

On the extensive margin, the fraction of households who farm rice peaks in 1999 and declines steadily thereafter. The exception is the last period of

category, this is not a big risk to validity.

the sample, where the fraction suddenly jumps again. One possible explanation comes from Panel B of Figure I, which plots median revenues, factor employment, and the international rice price. Anecdotal reports implicate the food price spike of 2008 in a temporary reversal in the steady decline of rice farming as a profession. An alternative explanation is that the global recession caused job loss in manufacturing and migration back to villages. Regardless of the cause, the sharp decline in median factor utilization that accompanied the surge in farming implies that this retrenchment was apparently mostly on the extensive margin as many individuals started small rice farms. Meanwhile, the plot for land confirms rural Thailand's uniquely incongruous mixture of fairly modern farming with relatively stable and small (fifteen rai, on average) landholdings. Finally, it is interesting to note that in the median, capital and labor, the two most easily adjustable factors in rice farming, move proportionally almost one-for-one across time, giving the naive impression of optimal factor usage.[13] But as will be seen in subsequent sections, the aggregates hide fascinating inter-firm variation.

5. Results

5.1. Estimated Production Function

Table II reports the results from estimating the production function using various different specifications that are valid under different assumptions. For future reference, let $\sigma = \alpha + \beta + \lambda$ denote the production function's returns-to-scale. Column 1 is a naive OLS regression, which assumes that farmers simply do not base their input choice on time-invariant productivity. Based on this regression, one might discard the implicit assumption of decreasing returns ($\sigma < 1$) in favor of constant returns ($\sigma = 1$).[14] But (2), which controls for time-invariant productivity, implies that OLS overestimates factor shares because they are indeed positively correlated with TFP. After controlling for the fixed-

[13] If the production function is isoelastic and exhibits constant returns in labor and capital.

[14] The consistency and closed form allocation results from Section 3.1. all require decreasing returns to be valid. In particular, if firms have varying TFP and constant returns in production, then one would expect in complete contingent markets for there to be only a single firm rather than a distribution of firm sizes.

effect, σ falls well below one. (3) adds province-year dummies and (4) adds anticipated TFP modifiers as defined in Appendix A, the main effect of which is to reduce the relative importance of capital versus land (though the difference is not significant). Finally, (5) implements the sequential exogeneity assumption outlined in Section 3.4.. The first-stage results of this latter specification indicate that the F/Wald statistics on the excluded instruments in the capital, land, and labor regressions are 105.9, 107.1, and 143.9, respectively - easily meeting the standard rules of thumb for instrumental strength (see Appendix A1. for full results).

[Table II around here]

5.2. Factor Allocative Efficiency in the Cross Section and Time Series

Panel A.1 of Figure II depicts kernel density estimates of $\hat{E}_{\hat{I}_t}$ at the village-level across three different years, where interchangeability is defined over all contemporaneously rice-farming firms for whom a fixed-effect is calculable (specifically, those who report positive levels of rice revenue and all factors in a given year and are observed doing so at least twice in the panel). $\hat{E}_{\hat{I}_t}$'s distribution is bounded below by zero and generally does not rise above one (and only ever does due to the small sample phenomena mentioned in Section 3.1.).[15]

The general upward shift in overall efficiency is unmistakable. Between 1996 and 2002, the modal $\hat{E}_{\hat{I}_t}$ increases and much of the movement is due to weight being shifted from the lower tail. Moreover, the variance appears to be collapsing in an interesting convergence in levels of efficiency. Both effects match intuition, as Thailand has been developing rapidly. However, although modal $\hat{E}$ rises even further from 2002 to 2008, the dispersion of village-level efficiency rises dramatically.

Panel B.1 of Figure II, which depicts various percentiles of the distribution and its expectation over time, may provide some answers. Although the gap between the bottom and top quartiles of the distribution narrowed between 1996

[15]The year 1996, as will be highlighted in Section 5.5., was characterized by atypically large unanticipated shocks. This might explain the abundance of villages with above-optimal allocations in that year.

and 2007 (albeit haltingly at times), this trend reversed in 2008 to accompany a fall in the median. Recall that by my dating convention, the year "2008" actually refers to the time span from May 2008 to April 2009. That twelve-month period was sufficiently eventful (featuring both the global financial crisis and the international food price spike) that any number of atypical shocks might be responsible for the reversal. What is notable is that the bottom quartile is hit much harder than the top, explaining the increased variance.

To quantify the lost output due to misallocations, one can calculate the potential gains from optimal reallocation. In 1996 the median $\hat{E}$ implies observed output is 84.7% of optimal output or potential gains from reallocation of about 18.1%, while by its peak in 2007 the median is about 94.4%, implying potential gains have fallen to 6.0%.

[Table III around here]

Table III explores the persistence of $\hat{E}_{\hat{I}_t}$ through autoregressions. Clearly, $\hat{E}_{\hat{I}_t}$ does show persistence, but somewhat less than one would expect (since the institutions responsible for inefficiency do not change rapidly). This is most likely an indication of how noisy a measure $\hat{E}_{\hat{I}_t}$ is of E_{I_t} - since most villages contain only about nine rice farmers as per the sample definition, the variance of the estimator is undoubtedly large.

5.3. Do Factor Market Failures or Financial Market Failures Matter More?

Upward shifts in the distribution of overall allocative efficiency, however, could come from many sources, and only by decomposing efficiency can the relative importance of each market friction be assessed. Panels A.2 and B.2 of Figure II depict the estimated densities of $\hat{E}^{FAC}_{\hat{I}_t}$ for several years and the evolution of the distribution's expectation and quantiles over time, with Panels A.3 and B.3 serving analogously for $\hat{E}^{FIN}_{\hat{I}_t}$. The sample is the same as that used to compute $\hat{E}_{\hat{I}_t}$ in Section 5.2..

The evidence indicates that the improvement of factor markets has been fairly uniform across the distribution. Starting in 1999, all parts of the distribution of $\hat{E}^{FAC}_{\hat{I}_t}$ have generally trended upwards until the aforementioned efficiency dip in 2008. This may be a reflection of the general trend noted in Section 4.3. where the fraction of rice farmers who report hiring labor and renting capital has risen dramatically since the beginning of the sample period. It is also possible that enforcement of land trading restrictions (as studies in Gine [2007]) has relaxed over the years. It is worth noting that even the efficiency dip of 2008 affected all the indicated quartiles roughly equally.

Not so financial markets if the distribution of $\hat{E}^{FIN}_{\hat{I}_t}$ is any guide. The time series plot shows that the different parts of the distribution are far less harmonized in their movements, with an interesting movement towards convergence from 1996 to 2003 that is subsequently reversed. The least efficient quartile not only shows stubbornly halting overall progress, but moreover higher variance. Perhaps most interestingly, the 2008 blip appears to have affected the quartiles differentially, with the top of the distribution hit hard while the lower quartiles actually continued their general upward trend. It is worth noting that by the end of the sample period, fully one quarter of the distribution of villages show a financial market efficiency above 1. This is likely because as these areas become more efficient, the variation in the upper quartile is less a reflection of true variation in efficiency and more a byproduct of the inherent stochasticity of the estimates of $\hat{E}^{FIN}_{\hat{I}_t}$ - either due to sampling error or simply because unanticipated TFP shocks will always ensure $\hat{E}_{\hat{I}_t}$ and $\hat{E}^{FIN}_{\hat{I}_t}$ are random.

Finally, Figure III, Panel A shows the (median) gains from perfecting factor markets, gains from subsequently perfecting financial markets, and the overall gains from perfecting both. As one would expect from the graphs of the efficiency measures, these are all falling despite starting at a relatively low base in 1996. It is worth re-emphasizing that under the assumption highlighted in Section 2.4., the gains from factor and financial market perfection are lower and upper bounds, respectively. Panel B, which shows the fraction of overall gains attributed to financial market perfection, shows that factor markets are not trivial in their contribution and that roughly 50-60% of the overall gains are generally due to them.

5.4. Allocative Efficiency and the Million Baht Program

The Million Baht Program, a massive and rapidly implemented injection of external loanable funds into village lending facilities in 2001, serves two valuable purposes in this analysis. First, it provides plausibly exogenous variation to allow a reduced-form estimate of the impact of credit availability on allocative efficiency. Second, it serves as a "reality check" for the source decomposition, as we would expect an increase in the supply of credit to operate on efficiency primarily through their effect on financial markets.

My approach is largely taken from Kaboski and Townsend (2009). The Million Baht Program provided additional money to village lending funds in all the villages in the Townsend Thai Annual Panel. Since every village received the same quantity of funds (one million baht), the per-household credit injection will be larger for smaller villages. The authors argue that "villages" in Thailand are in fact administrative units whose borders are the result of decisions made decades prior to the program for administrative convenience rather than socioeconomic considerations (see the original paper and also Kaboski and Townsend (2011) for more detailed justification of the instrument). Accepting that, the program-induced variation in the per-household credit injection is exogenous and represents quasi-randomization of the supply of credit.[16]

Taking their argument as true, I examine the reduced-form impact of the program on $\hat{E}$ and its decomposition. Unlike Kaboski and Townsend (2009), I define a binary indicator for whether a village is "small," defined as being in the bottom quartile for number of households, and use its interaction with an indicator for the years 2001 and 2002 (year of and year after program introduction) as the treatment. This is partly for ease of interpretation (the parameter is directly interpreted as a change in efficiency) and partly to avoid the truncation issue that would arise from applying a more continuous measure like the average credit injection to predict efficiency measures that are asymptotically bounded between zero and one.[17] Thus, the impact is estimated using a difference-in-differences approach where the impact is measured as the difference in the average observed change in $\hat{E}$ moving into 2001 between small and large villages after controlling for year and village fixed-effects. Before discussing the results, it is important to recall from Section 3.1. that standard er-

[16]Several models of financial market imperfections, e.g. Stiglitz and Weiss (1981), imply that increases in credit supply will alleviate credit market imperfections.

[17]Nevertheless, applying the average injection or the log average injection yields a very similar pattern in the coefficients, although standard errors are somewhat larger relative to point estimates.

rors on regressions of $\hat{E}$ and $\hat{E}^{FIN}$ are mechanically larger than those involving $\hat{E}^{FAC}$, as under isoelastic functional form $\hat{E}^{FAC}$ is invariant to realizations of ϕ.

[Table IV around here]

The results reported in Table IV indicate that small villages on average had all else equal 10.5% higher output due to improved factor allocative efficiency and that the difference is significant. Unfortunately, these effects on efficiency appear to have dwindled to insignificance within a year after the injection.

As predicted, the program's effect on $\hat{E}^{FIN}$ is somewhat larger than the effect on $\hat{E}^{FAC}$ as measured by coefficient estimates, and the point estimates indicate that 80.5% of the increase in overall efficiency is due to the financial market efficiency measure. In this regard, the decomposition is capturing what we would expect. Puzzlingly, however, there is a significant effect on $\hat{E}^{FAC}$ as well. One possibility is that this is a direct effect - for example, if some entrepreneurs used newly available funds to start capital rental businesses. If this is true, however, the implication of the estimates is that these businesses were not very successful - otherwise, one would expect some non-negligible effect the following year unless this was simply short-term arbitrage. It is worth noting that even the effect on $\hat{E}^{FIN}$ falls as well moving into the second year, implying all of the programs allocative effects dissipated rapidly.

Finally, it is interesting to note that the program's effects on rice production are largely allocative rather than accumulative (i.e. due to the employment of more productive factors). The latter three columns of Table IV confirm that the program had no statistically significant effects on the aggregate stocks. This null effect accords with the findings in Kaboski and Townsend (2011), which finds that detecting impacts on average investment would be difficult due to heterogeneity in behavior. Indeed, the implication of the present analysis is that increased investment by more productive firms roughly offset decreased investment by less productive ones, leaving the average unchanged.

5.5. Output and Growth Decompositions

Note that the assumption of isoelasticity inevitably implies Hicks-Neutral technological progress, and so Propositions 2 and 4 obtain. Taking a province as the aggregation unit of choice, the propositions imply

Table A.I
Sequential Exogeneity, First Stage

	(1) Δ Log(Capital) b/se	(2) Δ Log(Land) b/se	(3) Δ Log(Labor) b/se
Lagged Factors:			
- Capital	0.034***	-0.265***	0.061***
	(0.01)	(0.02)	(0.01)
- Land	-0.301***	0.055***	0.068***
	(0.02)	(0.02)	(0.01)
- Labor	0.044***	0.061***	-0.530***
	(0.01)	(0.02)	(0.03)
A:			
- Hunger	-0.006	-0.125**	0.048
	(0.05)	(0.06)	(0.05)
ϕ:			
- Illness	0.011	-0.046	0.090*
	(0.05)	(0.06)	(0.05)
- Death	0.060	-0.014	-0.167*
	(0.06)	(0.08)	(0.09)
- Flood	0.027	-0.049	-0.016
	(0.02)	(0.03)	(0.02)
- Pests	-0.016	0.028	0.042
	(0.03)	(0.04)	(0.03)
- Bad Rain	0.013	-0.047**	-0.020
	(0.02)	(0.02)	(0.02)
- Low Yield	-0.013	0.016	-0.015
	(0.02)	(0.02)	(0.02)
- Low Price	-0.037**	0.002	-0.011
	(0.02)	(0.02)	(0.02)
Precipitation	X	X	X
Year FEs	X	X	X
HH FEs	X	X	X
Year-District FE	X	X	X
nHH	729.000	729.000	729.000
NT	4803.000	4803.000	4803.000
F-test: Lagged Factors	107.065	105.938	143.899
P-value: Lagged Factors	0.000	0.000	0.000

Table A.II
CES Production Function Estimates

	(1) NLS b/se	(2) NLS b/se
ϵ	1.019	1.012
	(0.0073)	(0.0059)
σ	0.775	0.770
	(0.0391)	(0.0414)
α	0.301	0.307
	(0.0092)	(0.0044)
β	0.379	0.320
	(0.0117)	(0.0082)
ϑ	0.000	0.000
	(0.0000)	(0.0000)
ζ		1.026
		(0.0377)
λ_F		0.515
		(0.0134)
N	770.000	770.000
NT	6175.000	6175.000
Pval: $\epsilon = 1$	0.010	0.035
Pval: $\zeta = 1$		0.482
Pval: $\lambda\_F = .5$		0.277

Note: Estimated using fixed-effects nonlinear least-squares. Standard errors are bootstrapped with resampling at the household-level.

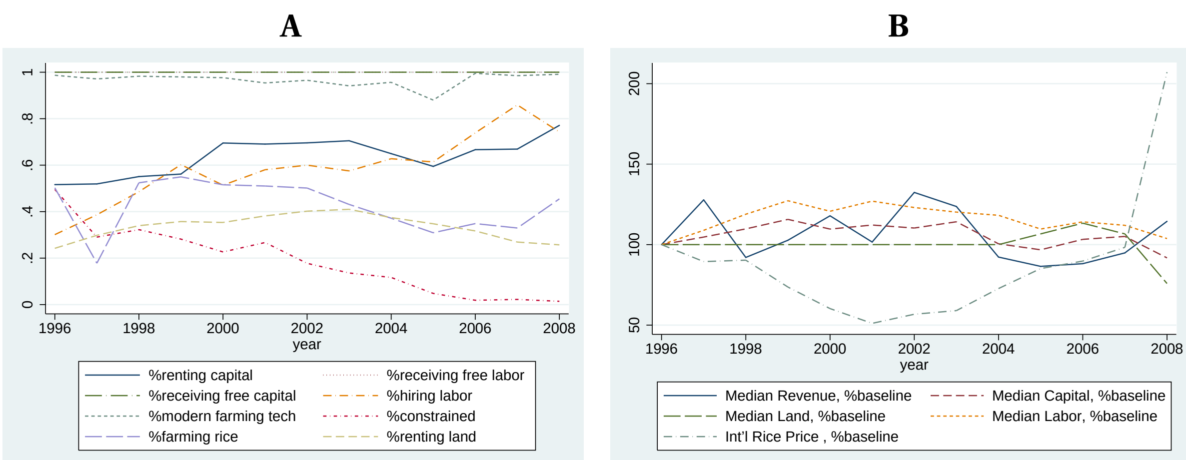
Table A.III
Predictors of Anticipated TFP

	(1)	(2)	(3)	(4)
	log $\hat{A}$	log K	log T	log L
	b/se	b/se	b/se	b/se
Schooling	0.018**			
	(0.01)			
Rice Suitability	0.086***			
	(0.02)			
Head's Age	-0.004**			
	(0.00)			
log $\hat{A}$		0.428***	0.453***	0.078***
		(0.05)	(0.03)	(0.02)
Constant	6.610***	7.780***	-0.409**	4.408***
	(0.13)	(0.33)	(0.19)	(0.17)
N	770.000	770.000	770.000	770.000
NT	5696.000	6173.000	6173.000	6173.000

Note: Regression should be interpreted as correlational. All standard errors clustered by household; regression standard errors in (2),(3), and (4) are NOT corrected for generated regressors. In (1), schooling represents the number of grades beyond kindergarten the household head has completed, where someone who has completed any grades in secondary school (Matthayom) is assumed to have completed six years of primary school (Prathom), anyone who has completed university education of any level is assumed to have completed six years of secondary school, and anyone who has completed any years of vocational training is assumed to have completed three years of secondary school.

Figure I

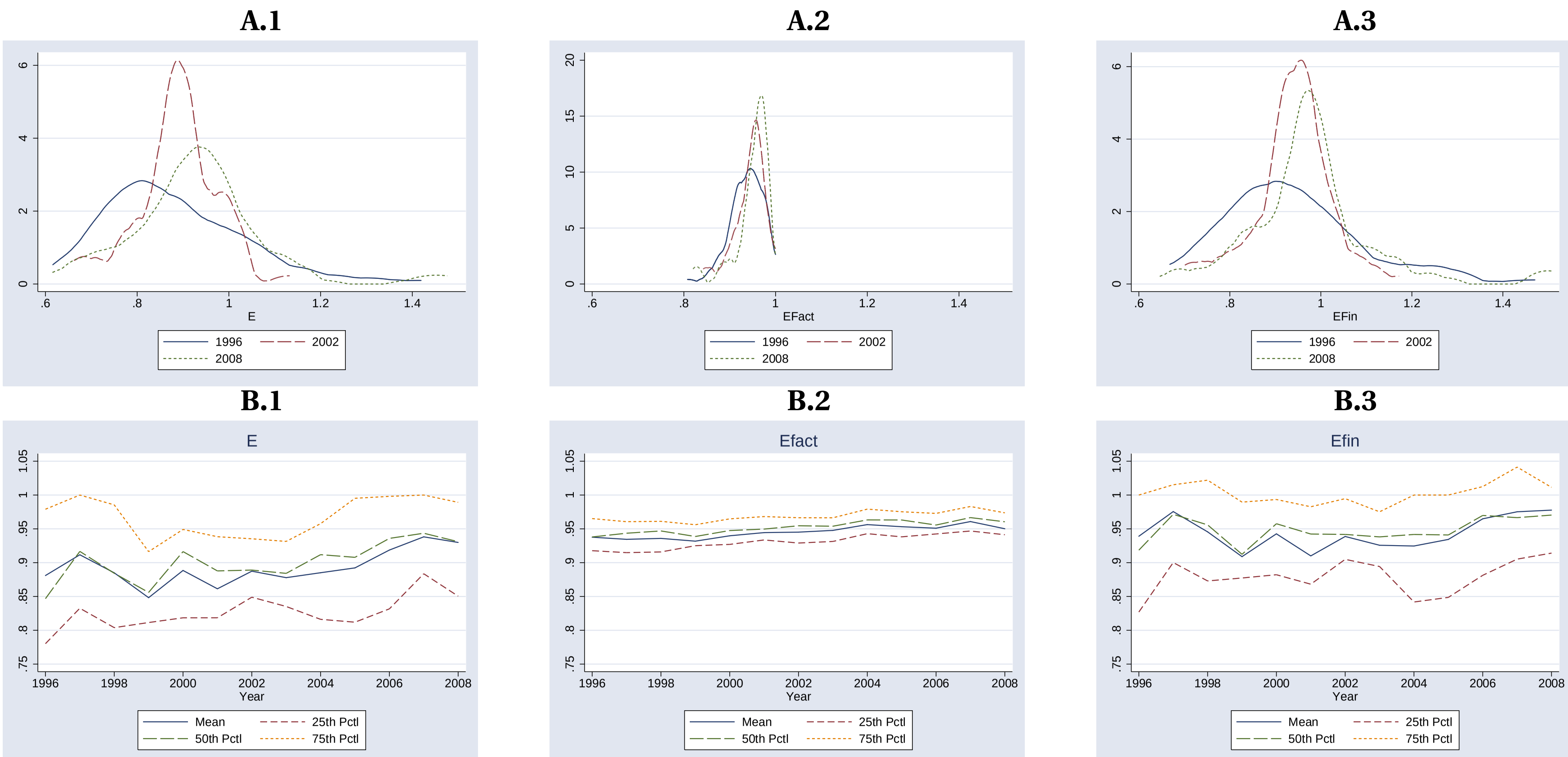
Panel A: Aggregate Time Series Plots of Descriptive Data, **Panel B:** Aggregate Time Series Plots of Rice Revenue, Factors, and Price



Note: **Panel A:** Percent farming rice is calculated as the fraction of the sample who report both positive revenues from rice and cultivation of land for rice. All other percentages are calculated conditional on farming rice as just defined. A firm is tagged as using "modern farming tech" if it reports using positive quantities of either fertilizer or pesticides. A firm is tagged as "constrained" if it reports being prevented from profitable expansion by either financing or factor hiring constraints. **Panel B:** Revenues and factors utilized are medians conditional on rice farming, and price is the Thailand nominal quote price. All variables are converted into fractions of baseline.

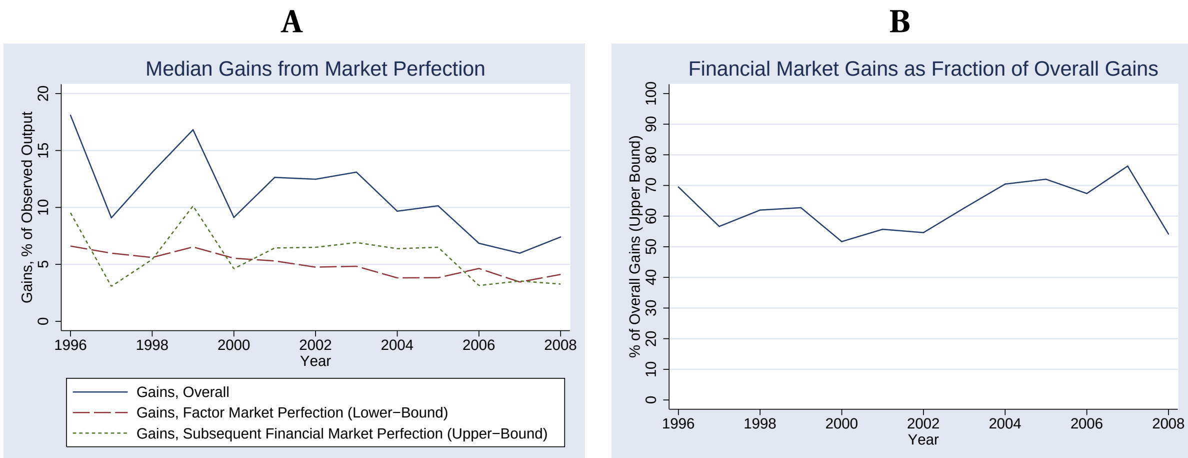
Figure II

Panel A: Density Estimates of $\hat{E}$, $\hat{E}^{FAC}$, $\hat{E}^{FIN}$ for different years. **Panel B:** Expectation and Percentiles of $\hat{E}$, $\hat{E}^{FAC}$, $\hat{E}^{FIN}$ over time.



Note: $\hat{E}$, $\hat{E}^{FAC}$, $\hat{E}^{FIN}$ are calculated at the village-level for each year on all farmers in the village who 1) farmed rice that year (reported positive rice revenue and levels of all three factors), and 2) farmed rice at least twice in the panel (so a fixed effect could be calculated).

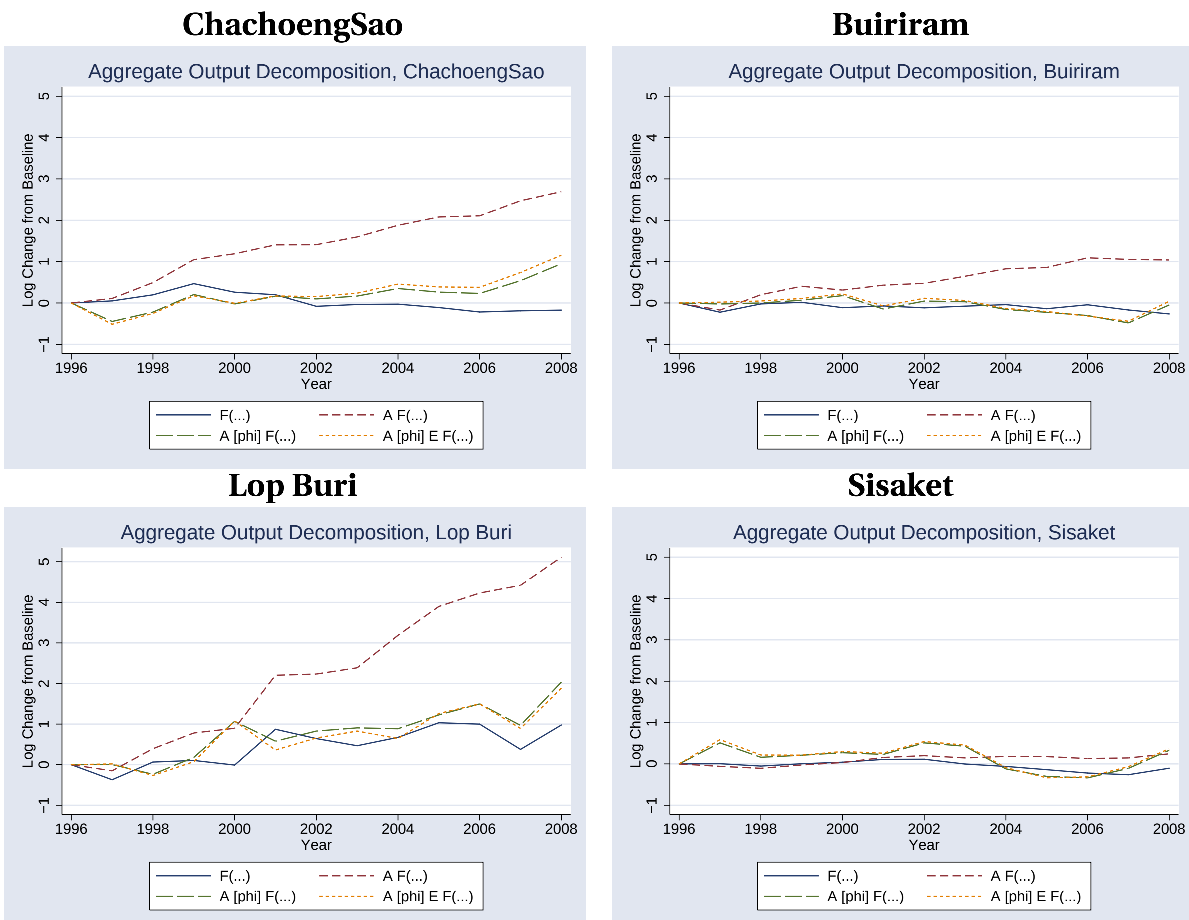
Figure III
Gains and Bounds on Gains from Reallocation



Note: **Panel A:** Under the assumptions of Section 2.4., the calculated gains from factor and subsequent financial market perfection are upper and lower bounds. **Panel B:** The fraction of overall gains attributed to financial market perfection (remainder is due to factor market perfection). Note that this is an upper bound as per Section 2.4..

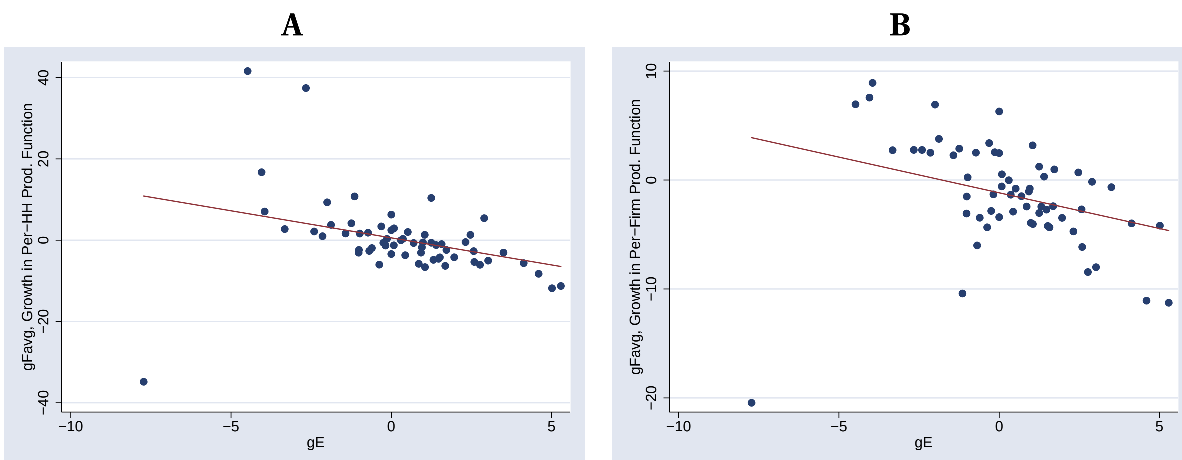
Figure IV

Province-Level Output Decompositions



Note: Decompositions of the real value of aggregate rice output at the province-level, defined in Proposition 4 and estimated as per Definition 14, and depicted as changes in the log from baseline. Each line allows the indicated components of aggregate output (see legend) to vary while holding the other components fixed at their 1996 levels. A refers to average technical efficiency, [phi] to the overall TFP shock ϕ, E to measured factor allocative efficiency, and F to the aggregate production function (where F is a function of aggregate factor stocks in each village assuming no interchangeability between villages - see Proposition 4 and the related discussion in Section 2.2.).

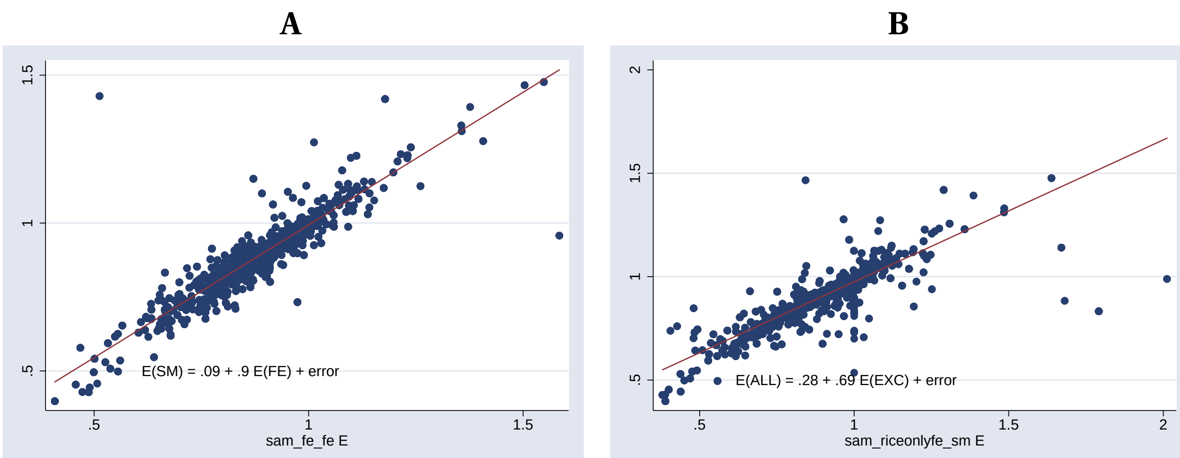
Figure V
Efficiency and Accumulative Growth



Note: Scatter plot of growth in allocative efficiency versus growth in **A)** aggregate ($\mathcal{F}$) and **B)** per firm (F) factor accumulation. Both plots exclude a single outlier with an atypically negative g_E value.

Figure A.I

Panel A: $\hat{E}$, Different Factor Shares; **Panel B:** $\hat{E}$, Different Samples



Note: Both panels plot $\hat{E}$ as calculated in the rest of the paper (y-axis) against some alternative specification (x-axis). Panel A calculates $\hat{E}$ while varying $\hat{\alpha}$, $\hat{\beta}$, $\hat{\lambda}$. Calculations using the estimates by fixed-effects (Column 4 of Table II) are on the x-axis while those using the sequential exogeneity estimates (Column 5 of Table II) are on the y-axis. Panel B calculates $\hat{E}$ while varying the reallocation sample. The x-axis uses only individuals who exclusively farm rice in a given year and for whom a fixed-effect can be estimated while the y-axis drops the criterion that they farm rice exclusively.