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# Productivity and misallocation during a crisis: Evidence from the Chilean crisis of 1982 ☆

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ABSTRACT

Measured total factor productivity often declines sharply during financial crises. In 1982, the Chilean manufacturing sector suffered a severe contraction in output, most of which can be accounted for by a falling Solow residual. This paper uses establishment data from the Chilean manufacturing census to examine the decline in measured TFP. To quantify the contribution of resource misallocation, I develop a measure of allocational efficiency along the lines of Hsieh and Klenow (2009) and derive the appropriate measure of aggregate productivity to which it should be compared. Across specifications, within-industry allocational efficiency either remained constant or improved in 1982, while a decline in between-industry allocational efficiency accounts for about one-third of the reduction in TFP. Industries more sensitive to domestic demand – durables and industries with low exports – experienced larger declines in measured TFP. This finding is consistent with large adjustment costs and underutilization of inputs. Reduced capital utilization played a substantial role, accounting for 25–50 percent of the decline in measured TFP.


Both output and measured total factor productivity decline sharply during financial crises. Calvo et al. (2006) analyze 22 severe crises in emerging markets and find that output and TFP typically decline by 10% and 9.5%, respectively. In 1982, Chile suffered a severe economic crisis. Output declined, unemployment rose, and capital inflows came to a halt. The contraction of the manufacturing sector was particularly severe, with output shrinking more than 20% and measured total factor productivity falling by more than 10%.

Understanding the changes at both the macro and micro levels can help distinguish between various theories of the crisis. This study uses establishment data from a comprehensive census of the Chilean manufacturing sector to investigate the large decline in measured TFP.

I first assess the role of misallocation of resources. One way to quantify the impact of allocational efficiency is to measure how much output could be gained by reallocating capital and labor across plants, in the spirit of Hsieh and Klenow (2009).[1] In this framework, allocational efficiency can be split into within- and between-industry components. The within-industry component measures total output as a fraction of the output that could be attained if capital and labor were reallocated

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[1] Such a measure has nothing to say about the source of misallocation, which could stem from any combination of adjustment costs, financing frictions, information issues, measurement error, or a host of other factors. Nevertheless, the time series of allocational efficiency can give clues about the source of aggregate fluctuations. See Chari et al. (2007) and Buera and Moll (2012) for further discussion.

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optimally within each industry. The between-industry component measures the latter as a fraction of output that could be attained by further reallocating capital and labor optimally across all plants.

During the crisis, within-industry allocation efficiency either stayed constant or improved. In contrast, between-industry allocational efficiency deteriorated, accounting for about one-third of the decline in TFP in 1982.

Variation in outcomes across industries can be used to assess the importance of various mechanisms. Industries which are more sensitive to domestic demand, those that produce durable goods and those that export less, experienced larger declines in measured TFP. A decline in demand, on its own, would not reduce an industry's productivity. However, plants that find it costly to adjust capital or labor may underutilize these inputs, reducing measured productivity. There is also suggestive evidence that deteriorating financial conditions raised the cost of working capital used to finance imported inputs.[2]

To shed light on the decline in between-industry allocational efficiency, I construct indices that measure reallocation of capital, labor, and value added across industries. There is a large increase in reallocation of value added between industries during the crisis, as industries had different levels of exposure to the large changes in domestic demand and financial conditions. A smaller increase in reallocation of labor and close to normal levels of reallocation of capital during the crisis are consistent with adjustment costs preventing reallocation of capital and labor from fully matching the shifting industry conditions.

Finally, I assess the contribution of factor utilization. If capital services require fixed proportions of energy and capital, capital utilization can be measured using energy consumption. Under the assumption that all plants require the same energy per unit of capital, declining capital utilization can account for roughly one-third of the decline in measured TFP in 1982. However, industries that tend to use less energy per unit of capital saw larger declines in energy usage. Using less energy could reflect a lower rate of utilization or a lower energy requirement per unit of capital. If it reflects the latter, the decline in capital services would be larger than implied by the change in aggregate energy consumption. Under the alternate assumption that industries differ in energy requirements, an approximation around uniform rates of utilization indicates that declining utilization can account for 45–50% of the decline in measured TFP.[3]

This study is related to the growing literature that explores the link between the allocation of resources across plants and measured TFP. Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and Banerjee and Duflo (2005) propose plant-level misallocation as an explanation for cross-country income differences. The most closely related studies are Wright and Sandleris (2011), who study the Argentine Crisis of 2001 and find that half of the decline in measured TFP can be accounted for by a deterioration in the allocation of resources; and Ziebarth (2012), who studies changes in within-industry allocational efficiency of several U.S. industries during the Great Depression.

In quantifying the impact of allocational efficiency, the two most serious confounding issues are measurement error and specification error. The most prominent measurement issue is that capital is notoriously difficult to measure. The extent of misallocation will be overstated if capital is poorly measured. It is especially important to keep this in mind when interpreting the level of output losses from misallocation. This paper studies changes in allocational efficiency over time and relies on the assumption that the extent of measurement error does not change systematically during the crisis.[4]

Specification of production functions at the micro level raises other issues. Because plants' marginal products cannot be measured directly, the measures of allocational efficiency lean heavily on the functional forms of plants' production functions. A notable feature of the establishment data is that there are large persistent differences in capital intensity across plants, even within narrowly defined industries. It is possible that these differences stem from persistent distortions (e.g., some plants have a long-term source of inexpensive capital), but it is also possible that plants simply use different production technologies. This matters because if the differing capital intensity reflects differing technologies, there is little to gain from reallocating resources across plants. I consider empirical specifications spanning these extremes.

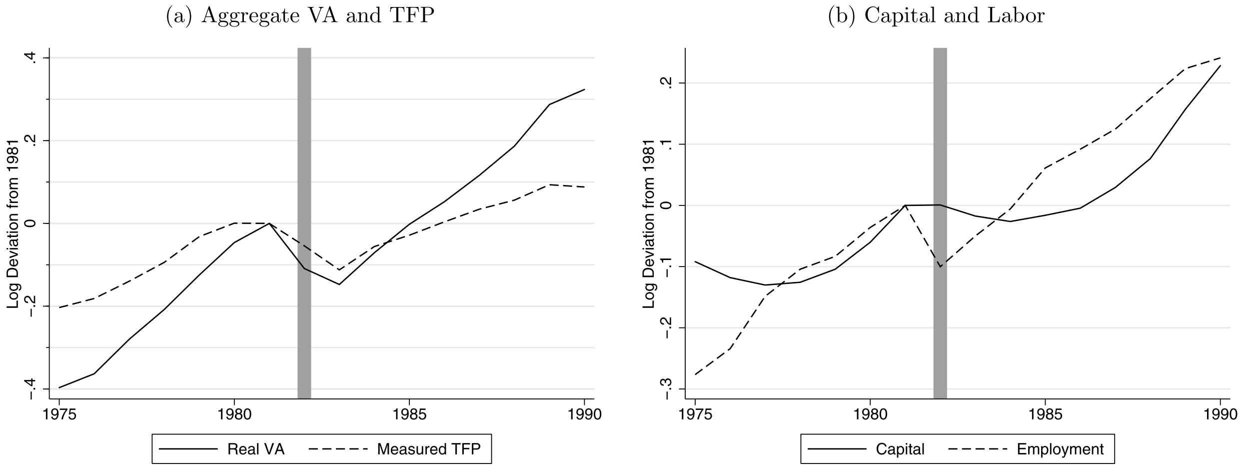
The benefit of assuming plants differ in factor intensities is that it relaxes a restrictive assumption that could lead to overstating the extent of misallocation. The cost of the assumption is that it raises aggregation issues. A central goal of this exercise is to better understand changes in aggregate output.[5] To make the analysis compatible with growth accounting at the aggregate level, and in particular with changes in aggregate capital and labor, I take care to compare the changes in the

[2] Mendoza and Yue (2012) and Pratap and Urrutia (2012) argue that a working capital constraint can raise the effective cost of intermediate inputs. In Mendoza and Yue (2012), only imported intermediates require working capital, so that the crisis induces imperfect substitution to locally produced intermediates. Kim (2011) introduces a wedge between the price of imports at the dock and the cost of the inputs to a firm, and argues that this helps explain the decline in measured TFP during the Korean crisis of 1997–1998. Gopinath and Neiman (2012) show that during the Argentine crisis in 2001–2002, many firms reduced imports of intermediate materials. They argue that substitution to locally produced intermediate inputs (and mismeasurement of the cost of input bundles) can quantitatively explain the large decline in measured TFP.

[3] The relatively small contribution of capital utilization when the change in capital services is measured using aggregate energy usage is in line with the findings of Meza and Quintin (2007). Those authors argue that declining capital utilization can only explain a small fraction of the decline in measured TFP during Mexico's crisis in 1994, and attribute much of the decline to increased labor hoarding. In contrast, Otsu (2008) and Gertler et al. (2007) attribute the decline in TFP during the Korean crisis of 1997–1998 to decreased capital utilization. Meza and Quintin (2007) conjecture that the Korean labor market was more flexible, so that labor hoarding was less prevalent.

[4] While this assumption is strong, it is considerably weaker than that needed to compare misallocation across countries that use different surveys. Hsieh and Klenow (2009) provide evidence indicating their findings are not driven by measurement error alone.

[5] Basu and Fernald (2002), Basu et al. (2012), and Wright and Sandleris (2011) show that an appropriately modified Solow residual is the relevant summary statistic for a first-order approximation of welfare even when it does not properly measure technology. I take an alternative approach closer to Solow (1957) and construct a residual to account for changes in output rather than to approximate changes in welfare.




*Note*: Panel (a) shows value added and TFP for the Chilean economy as a whole, while panel (b) shows aggregate quantities of the capital and labor. All series are in logs with 1981 normalized to zero. Measured TFP is $\frac{VA}{K^{\alpha}L^{1-\alpha}}$ with $\alpha = 0.45$. Capital is constructed using perpetual inventory method assuming 10% depreciation. The initial capital stock in 1960 is constructed by assuming investment prior to 1960 grew each year at the average rate of 1960–1964. Source: WDI and author's calculations.

**Fig. 1.** Aggregate production.

extent of misallocation to the appropriate Solow residual. I show that if the Solow residual is computed using capital and labor shares of the "efficient" aggregate production function, it can be cleanly decomposed into changes in allocational efficiency and changes in "technology" (a summary statistic for the distribution of plant-level productivity parameters). Notably, these factor shares depend on the specification of underlying plant level technology.[6] When plants have heterogeneous production functions, these factor shares depend on the joint distribution of plant-level productivities and factor intensities, as well as the aggregate capital–labor ratio.[7]

Section 1 discusses the economic environment and the impact of the recession, and Section 2 describes the data. Section 3 develops measures of allocational efficiency, while Section 4 applies them to the Chilean manufacturing census. Section 5 discusses some explanations for differences in outcomes across industries. Section 6 assesses the contribution of capital utilization and labor hoarding, and Section 7 concludes.

## 1. Reform and recession in Chile

In the decade prior to the crisis, Chile's economic landscape underwent drastic changes. The military government that took power in 1973 instituted a number of reforms. In 1974, the Chilean government privatized the nation's banks. Several were subsequently bailed out after poor performance in 1976–1977. The banks were primarily in private hands until the crisis in the early 1980s, when several banks had to be bailed out again. To tackle runaway inflation, the government instituted a series of planned currency devaluations relative to the dollar in 1978 that culminated in the establishment of a fixed nominal exchange rate with the dollar in 1979. The fixed rate remained in place until June 1982, in the middle of the recession. In 1973, import tariffs were large and varied widely, averaging 105%. There were also many non-tariff trade barriers. From 1973 to 1979, these trade barriers were gradually reduced to a uniform tariff of 10%.[8] While labor market regulations were liberalized, at the onset of the crisis there were still substantial barriers to mobility.[9]

Following these reforms, the Chilean economy experienced rapid growth and a massive influx of capital in the late 1970s, but suffered a large contraction in 1982. Fig. 1 shows the large decline in value added and TFP for the Chilean economy as a whole, using data from the World Bank's World Development Index.

Fig. 2(a) shows the evolution of value added for each sector of the economy. The contraction of the manufacturing sector was particularly severe; although manufacturing accounted for roughly one-fifth of the Chilean economy, it accounted for

[6] Put differently, specification of micro technology provides a resolution to the usual difficulty in constructing Solow residuals of whether to use a capital share of roughly 0.35 (usually justified by appealing to evidence from Gollin, 2002) or a capital share closer to 0.5, closer to the aggregate cost share of capital in Chile.

[7] Most studies using the Hsieh and Klenow (2009) methodology avoid this issue by comparing differences in the extent of misallocation with differences in aggregate output rather than with differences in aggregate TFP.

[8] This liberalization was subsequently reversed in the aftermath of the crisis, with average tariff rates rising to 26% by 1985 (Dornbusch and Edwards, 1994).

[9] From 1973 through 1979, nominal wages for some workers were periodically adjusted for increases in the CPI through legislation. In 1979, this was extended to all workers. Any new wage offers had a floor of the previous wage multiplied by the change in CPI since the previous wage offer. Another reform in 1978 attempted to reduce hiring frictions by eliminating the "just cause" doctrine, and in 1981 severance payments were capped at five months. Frictions remained sizable, as severance was equal to one month for every year worked (up to this five-month cap).


*Note*: Panel (a) shows the log of value added for various sectors with 1981 normalized to zero. Note that Manufacturing is a subset of Industry. Panel (b) shows total exports and imports as a percent of 1981 Chilean GDP. Source: WDI.

**Fig. 2.** Aggregate production.

roughly two-fifths (41%) of the decline of total real value added between 1981 to 1982. In 1983, the manufacturing sector began to recover. Fig. 2(b) shows total exports and imports. While imports cratered during the crisis, exports were fairly stable.

For further descriptions of the Chilean experience before, during, and after the recession, see the excellent summaries in Diaz-Alejandro (1985) and Bosworth et al. (1994).

## 2. Plant-level data

### 2.1. Data description

Plant-level data comes from a high-quality annual census of the manufacturing sector, Encuesta Nacional Industrial Anual (ENIA) conducted by the Instituto Nacional de Estadisticas, spanning the years 1979 to 1996. The survey covers all manufacturing plants with at least 10 employees and has been used by numerous other studies.[10] The dataset is an unbalanced panel with nearly 5000 unique observations each year. The survey collects data on revenue, blue and white collar employment and wages, intermediate inputs, as well as investment, sales, and depreciation of several types of capital. Entry and exit from the dataset does not correspond to actual entry and exit; a plant that shrinks to nine employees would not show up in the data. Indeed, some plants disappear in one year only to reappear a year or two later. The survey contains no information linking plants to firms, though the vast majority of plants belong to single-plant firms.[11]

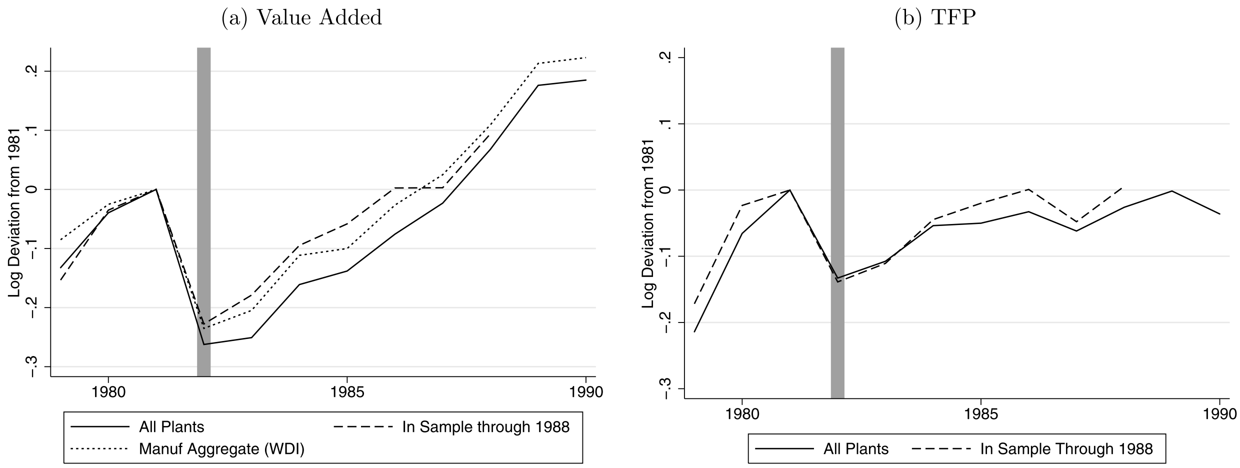
The largest difficulty in this study is the construction of plant-level capital variables. The survey collects information on investment and depreciation of several types of capital (machines, buildings, and vehicles) and rental payments that must be aggregated. This paper uses real capital services as constructed by Greenstreet (2007). Greenstreet (2007) constructs real capital stocks for each of the three types of capital using the perpetual inventory method, assuming depreciation rates of 5%, 10%, and 20% for buildings, machines, and vehicles, respectively. The procedure uses reported nominal investment and capital price deflators for each type of capital from Bergoeing et al. (2003). Initial capital stocks are backed out from reported depreciation and investment in the first year. Real rental rates for each type use the respective depreciation rates and nominal interest rates (lending and deposit rates from the IMF give virtually identical results). These rental rates are then averaged over time. Real capital services are the sum of the individual capital stocks weighted by the respective average rental rates[12] corrected for the portion of the year the plant was open, plus the real value of reported rental payments (deflated using the CPI).[13]

[10] Among the many, see Liu (1993), Roberts and Tybout (1996), Pavcnik (2002), Fuentes et al. (2006), Greenstreet (2007), Petrin and Levinsohn (2010), Bergoeing et al. (2010), and Petrin and Sivadasan (2011).

[11] Hsieh and Parker (2007), using information provided by the INE, report that most plants in the dataset are themselves firms. In 1984, approximately 350 plants belonged to multi-plant firms, under 10%.

[12] Time-averaged rental rates are used so that a change in capital services can come only from changes in stocks of each type of capital, not changes in weights.

[13] See Appendix D in Greenstreet (2007) for more information on the construction of these capital stocks. In some years, the survey collects information on the value of fixed assets of each type. Greenstreet (2007) reports that among plants that were in the survey in those years, the constructed capital stocks and the deflated fixed asset values match well.




*Note*: Panel (a) shows value added for the manufacturing sector by three measures. The line labeled "All plants" shows aggregate value added among all plants in the manufacturing census, while "In Sample through 1988" restricts the sample to a balanced sub-panel of plants that were in the survey for the first ten years of the sample period, 1979–1988. The line labeled "Manuf Aggregate (WDI)" shows value added for the manufacturing sector as reported by the World Bank. Panel (b) shows TFP among all plants and among the balanced sub-sample, using a capital share of $\alpha = 0.45$. All series are in logs with 1981 normalized to zero. Source: WDI, ENIA, and author's calculations.

**Fig. 3.** Aggregating plant level data.

As with most studies that use this data, I assume industries in the model correspond to three-digit industries in the data. A number of plants switch three-digit industries at some point, some shifting back and forth between two or more industries. While it is possible that switches reflect changes in goods being produced, they may also reflect errors in classification. To guard against the latter, I assign each plant to its modal three-digit industry, with ties broken by using the earliest mode. See Section B of the online appendix for descriptions and summary statistics for the various industries.

Plant-year observations are dropped if capital, payments to labor, or value added, are either non-positive or missing. If a plant has a non-positive or missing value in 1981 or 1982, the plant is dropped from the sample.

The plant exit rate is particularly high in the first several years of the panel, a fact attributed by Pavcnik (2002) to the increased openness toward the end of the 1970s. Several of the calculations are made using a balanced panel of plants that were in the sample for the first ten years of the survey, 1979–1988. This is not a perfect sample, as the age composition varies over time. However, the results using the balanced sub-panel are similar to those using the entire sample of plants, indicating that these patterns do not stem solely from entry and exit.

### 2.2. *Aggregating plant-level data*

The manufacturing census includes the universe of plants with at least ten employees. Fig. 3 compares the time series of value added using data from the census to value added for the manufacturing sector as reported in the WDI. Two of the series in Fig. 3(a) use plant-level data. The first is real value added among all plants in the dataset. The second shows real value added among plants that were in the sample for all of the first ten years, 1979–1988. All three series show a qualitatively similar pattern, a large contraction in 1982 followed by an immediate but slow recovery, although the plant-level data show a slightly larger drop in 1982.

With the establishment data, capital and labor can be aggregated across plants to compute a Solow residual for the manufacturing sector. Fig. 3(b) shows the Solow residual for the aggregate value-added production function using a capital share of 0.45, both for all plants and for the sub-panel of firms in the survey from 1979 through 1988. For each series, the Solow residual falls by roughly 13% and qualitatively matches the pattern of value added in the years around the crisis.

## 3. Accounting for allocational efficiency

To quantitatively assess the contribution of misallocation to the decline in measured TFP, I develop an accounting procedure that separates changes in an aggregate Solow residual into changes in productivity and changes in allocational efficiency. The decomposition measures deviations from a frictionless optimum using strong functional-form assumptions in a manner similar to Hsieh and Klenow (2009).

Strictly speaking, an increase in the extent of measured misallocation does not necessarily imply inefficiency in the constrained sense, as deviations from a frictionless optimum may be due to a variety of frictions. For example, if plants face investment adjustment costs, a planner facing those same adjustment costs might not be able to raise output by reallocating resources. Nevertheless, the goal is to account for changes in the aggregate Solow residual (which itself accounts for changes in aggregate output). To this end, one should interpret the decomposition as an accounting exercise that can provide clues about the sources of changes in aggregate output.

Consider an economy composed of many industries. Each industry is composed of plants that produce differentiated products that are combined into an industry aggregate. Industry aggregates are then combined into a single aggregate good. Let $Y_i$ be the output of plant $i$, $Y_s \equiv (\sum_{i\in I_s} Y_i^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}$ be the quantity of the industry aggregate for industry $s$, and $Y \equiv \prod_{s\in S} Y_s^{\theta_s}$ be the quantity of the manufacturing aggregate with $\sum_{s\in S}\theta_s = 1$. These industry shares $\{\theta_s\}$ evolve over time. Price-taking consumers spend optimally. If $P_i$ is the price of the good produced by plant $i$, then $P_s \equiv (\sum_{i\in I_s} P_i^{1-\sigma})^{\frac{1}{1-\sigma}}$ and $P \equiv \sum_{s\in S}(\frac{P_s}{\theta_s})^{\theta_s}$ are ideal price indices for the industry good and aggregate good, respectively.

Plant $i$ has access to the production function $Y_i \leqslant A_i K_i^{\alpha_i} L_i^{1-\alpha_i}$.[14] As a special case, this nests the specification of Hsieh and Klenow (2009), in which all plants in an industry have the same capital intensity.

### 3.1. A frictionless allocation

Given the total quantity of capital and labor available in the economy, how much of the aggregate good can be produced? Formally, the maximum attainable output $Y^{**}$ is

$$\max_{\{K_i,L_i\}_{i\in I_s,\ s\in S}} \prod_{s\in S}\left[\sum_{i\in I_s}\left(A_i K_i^{\alpha_i} L_i^{1-\alpha_i}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}\theta_s}$$

subject to $\sum_{s\in S}\sum_{i\in I_s} K_i \leqslant K$ and $\sum_{s\in S}\sum_{i\in I_s} L_i \leqslant L$.

As shown in Section C of the online appendix, the maximum attainable output is

$$Y^{**} = \prod_{s\in S}\left(\sum_{i\in I_s}\left[A_i\left(\frac{\alpha_i}{\alpha^{**}}\theta_s K\right)^{\alpha_i}\left(\frac{1-\alpha_i}{1-\alpha^{**}}\theta_s L\right)^{1-\alpha_i}\right]^{\sigma-1}\right)^{\frac{1}{\sigma-1}\theta_s} \tag{1}$$

where $\alpha^{**}$ is defined to satisfy

$$\alpha^{**} = \sum_{s\in S}\theta_s \sum_{i\in I_s}\frac{\left[A_i(\frac{\alpha_i}{\alpha^{**}}K)^{\alpha_i}(\frac{1-\alpha_i}{1-\alpha^{**}}L)^{1-\alpha_i}\right]^{\sigma-1}}{\sum_{j\in I_s}\left[A_j(\frac{\alpha_j}{\alpha^{**}}K)^{\alpha_j}(\frac{1-\alpha_j}{1-\alpha^{**}}L)^{1-\alpha_j}\right]^{\sigma-1}}\alpha_i \tag{2}$$

There are several features to note. First, $\frac{\partial \ln Y^{**}}{\partial \ln K} = \alpha^{**}$ and $\frac{\partial \ln Y^{**}}{\partial \ln L} = 1-\alpha^{**}$, so that a first-order approximation of the frictionless aggregate production function is a Cobb–Douglas production function with capital share $\alpha^{**}$. This will be relevant when accounting for changes in output.

Second, the capital intensity of the frictionless production function, $\alpha^{**}$, is a weighted average of the capital intensities of individual plants, weighted by optimal size. As plants' productivities change, the aggregate capital intensity shifts to better reflect the capital intensity of the lower-cost plants.

Third, $\alpha^{**}$ depends on the aggregate capital–labor ratio. When capital is more abundant, capital-intensive plants' costs fall relative to those of labor intensive plants, increasing the optimal scale of the capital-intensive plants. This shift in composition makes the frictionless aggregate production function more capital intensive.

Lastly, with homogenous factor intensities among plants within each industry, as in Hsieh and Klenow (2009), the frictionless factor share depends only on parameters: $\alpha^{**} = \sum_{s\in S}\theta_s\alpha_s$. In that case, $\alpha^{**}$ only changes because of the evolution of the industry shares, $\{\theta_s\}$.

Another thought experiment involves reallocating capital and labor *within* industries rather than across the economy. Holding fixed capital and labor actually used by each industry, how much of the aggregate good can be produced? Formally, let $Y^* \equiv \prod_{s\in S}(Y_s^*)^{\theta_s}$ where $Y_s^*$ is

$$\max_{\{K_i,L_i\}_{i\in I_s}}\left[\sum_{i\in I_s}\left(A_i K_i^{\alpha_i} L_i^{1-\alpha_i}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

subject to $\sum_{i\in I_s} K_i \leqslant K_s$ and $\sum_{i\in I_s} L_i \leqslant L_s$. The maximum attainable industry aggregate is

$$Y_s^* = \left(\sum_{i\in I_s}\left[A_i\left(\frac{\alpha_i}{\alpha_s^*}K_s\right)^{\alpha_i}\left(\frac{1-\alpha_i}{1-\alpha_s^*}L_s\right)^{1-\alpha_i}\right]^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{3}$$

where $\alpha_s^*$ is defined to satisfy

$$\alpha_s^* = \sum_{i\in I_s}\frac{\left[A_i(\frac{\alpha_i}{\alpha_s^*}K_s)^{\alpha_i}(\frac{1-\alpha_i}{1-\alpha_s^*}L_s)^{1-\alpha_i}\right]^{\sigma-1}}{\sum_{j\in I_s}\left[A_j(\frac{\alpha_j}{\alpha_s^*}K_s)^{\alpha_j}(\frac{1-\alpha_j}{1-\alpha_s^*}L_s)^{1-\alpha_j}\right]^{\sigma-1}}\alpha_i \tag{4}$$

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[14] Throughout, variables with an $i$ subscript refer to plant $i$, variables with an $s$ subscript refer to aggregates for industry $s$, and variables with no subscript refer to aggregates for all manufacturing plants. Time subscripts are omitted unless necessary for clarity.

### 3.2. Misallocation and the Solow residual

This section shows that a particular Solow residual can be decomposed into changes in "technology" and changes in the extent of misallocation.[15] To do this, I first develop the relationship between the actual and efficient quantities of output. This can be separated into two parts, measuring allocational efficiency within and between industries:

$$M_W \equiv \frac{Y}{Y^*}$$
$$M_B \equiv \frac{Y^*}{Y^{**}}$$

$M_W$ measures the contribution of within-industry allocational efficiency to aggregate output and is closely related conceptually to the measures of Hsieh and Klenow (2009). When $M_W$ reaches 1, capital and labor are optimally allocated across plants within each industry. Similarly, $M_B$ measures the additional contribution to output of allocational efficiency between industries.

Next I turn to the frictionless aggregate production function given by (1). Changes in the efficient level of output can be decomposed into changes in aggregate capital, changes in aggregate labor, and a residual that reflects changes in technology, $d\ln A^{**}$:

$$d\ln Y^{**} = d\ln A^{**} + \alpha^{**} d\ln K + \left(1-\alpha^{**}\right) d\ln L$$

Putting these pieces together, changes in *actual* output can be decomposed into:

$$d\ln Y = d\ln M_B + d\ln M_W + d\ln A^{**} + \alpha^{**} d\ln K + \left(1-\alpha^{**}\right) d\ln L$$

This can be rewritten as

$$d\ln Y - \alpha^{**} d\ln K - \left(1-\alpha^{**}\right) d\ln L = d\ln M_B + d\ln M_W + d\ln A^{**}$$

The left-hand side gives a Solow residual that uses factor shares from the frictionless production function. These factor shares differ from cost shares that would be used in computing a standard Solow residual. Instead, they reflect what the cost share would be if capital and labor were reallocated optimally. Importantly, this particular Solow residual can be cleanly decomposed into changes in allocational efficiency and changes in technology.[16]

### 3.3. Measurement

This section describes how the measures of allocational efficiency, $M_W$ and $M_B$, and factor shares from efficient production, $\alpha^{**}$ and $\{\alpha_s^*\}$, are obtained from plant-level data. Given the expressions in Section 3.1, this is straightforward.

Optimal spending by the consumer requires $Y_i = Y_s(\frac{P_iY_i}{P_sY_s})^{\frac{\sigma}{\sigma-1}}$. Combining this with $Y_i = A_i K_i^{\alpha_i} L_i^{1-\alpha_i}$ gives

$$A_i = Y_s \frac{(\frac{P_iY_i}{P_sY_s})^{\frac{\sigma}{\sigma-1}}}{K_i^{\alpha_i} L_i^{1-\alpha_i}} \tag{5}$$

Plugging this into Eqs. (2) and (4) and rearranging yields

$$0 = \sum_{s\in S} \theta_s \sum_{i\in I_s} \left[ \left(\frac{P_iY_i}{P_sY_s}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{K/\alpha^{**}}{K_i/\alpha_i}\right)^{\alpha_i} \left(\frac{L/(1-\alpha^{**})}{L_i/(1-\alpha_i)}\right)^{1-\alpha_i} \right]^{\sigma-1} \left(\alpha_i - \alpha^{**}\right) \tag{6}$$

$$0 = \sum_{i\in I_s} \left[ \left(\frac{P_iY_i}{P_sY_s}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{K_s/\alpha_s^*}{K_i/\alpha_i}\right)^{\alpha_i} \left(\frac{L_s/(1-\alpha_s^*)}{L_i/(1-\alpha_i)}\right)^{1-\alpha_i} \right]^{\sigma-1} \left(\alpha_i - \alpha_s^*\right) \tag{7}$$

Obtaining each of these capital intensities requires solving a single non-linear equation in one unknown.[17]

Similarly, plugging (5) into Eqs. (1) and (3) along with $Y = \prod_{s\in S} Y_s^{\theta_s}$ yields

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[15] Technology is used loosely because changes may reflect shifts in relative demand, factor utilization, or the cost of materials.

[16] In the spirit of Hsieh and Klenow (2009), the measures of allocational efficiency, $M_W$ and $M_B$, and technology, $A^{**}$, take the composition of plants as given. Omitted from the exercise is the possibility that distortions affect the composition of plants: distortions could cause some productive plants to exit prematurely or allow the survival of unproductive plants. Yang (2011) estimates TFP losses from misallocation in Indonesia and finds these are substantially larger when he includes an extensive margin. While allowing for an extensive margin in this analysis would likely reduce estimates of the *level* of allocational efficiency, it is unclear a priori how it would affect *changes* during the crisis. In Section E.2 of the online appendix, the sample is restricted to plants that remained in the survey from 1979 to 1988, and the results are similar to the baseline specification. Still, this is a fruitful area for future research.

[17] This is easily generalized to production functions with $N > 2$ factors of production, in which case there would be a system of $N-1$ non-linear equation in $N-1$ unknowns.

$$\frac{Y^{**}}{Y} = \frac{1}{M_W M_B} = \prod_{s\in S}\left(\sum_{i\in I_s}\left[\left(\frac{P_i Y_i}{P_s Y_s}\right)^{\frac{\sigma}{\sigma-1}}\left(\frac{\theta_s K/\alpha^{**}}{K_i/\alpha_i}\right)^{\alpha_i}\left(\frac{\theta_s L/(1-\alpha^{**})}{L_i/(1-\alpha_i)}\right)^{1-\alpha_i}\right]^{\sigma-1}\right)^{\frac{\theta_s}{\sigma-1}} \tag{8}$$

$$\frac{Y^{*}}{Y} = \frac{1}{M_W} = \prod_{s\in S}\left(\sum_{i\in I_s}\left[\left(\frac{P_i Y_i}{P_s Y_s}\right)^{\frac{\sigma}{\sigma-1}}\left(\frac{K_s/\alpha_s^{*}}{K_i/\alpha_i}\right)^{\alpha_i}\left(\frac{L_s/(1-\alpha_s^{*})}{L_i/(1-\alpha_i)}\right)^{1-\alpha_i}\right]^{\sigma-1}\right)^{\frac{\theta_s}{\sigma-1}} \tag{9}$$

An appealing property of these measures is that they are unitless. This means that nominal value added, nominal payments to labor, and real capital services can be used to compute the portion of output lost to misallocation. An implication is that poorly measured deflators (likely in an environment with rampant inflation) for value added or payments to labor will not introduce additional measurement error. In addition, using price deflators that are common for an entire industry can mask differences in output and input prices facing different plants. These differences are precisely what the decomposition is attempting to uncover. Finally, expenditures on inputs can be used to control for differences in input quality. For example, the wage bill can be used to control for the quality of the workforce.

Note also that no assumptions are made regarding plants' choices of capital and labor. The only assumptions used are (i) the functional forms of each plant's production function; (ii) the functional form of the demand system; and (iii) price-taking consumers make optimal purchasing decisions. The framework takes no stand on how prices are set.

Finally, I define several terms that will be used later in characterizing allocational efficiency. If resources are allocated efficiently within industries, the ratio of value added to capital for plant $i$ satisfies $\frac{\alpha_i P_i^* Y_i^*}{K_i^*} = \frac{\alpha_s^* P_s Y_s}{K_s}$. Define the capital wedge of plant $i$ to be the deviation of this ratio from its efficient (within-industry) level: $T_{Ki} \equiv \frac{P_i Y_i/K_i}{P_i^* Y_i^*/K_i^*}$. Similarly, define the labor wedge to be $T_{Li} \equiv \frac{P_i Y_i/L_i}{P_i^* Y_i^*/L_i^*}$. Lastly, define the scale wedge for plant $i$ to be $T_i \equiv T_{Ki}^{\alpha_i} T_{Li}^{1-\alpha_i}$. A plant's scale wedge is related to its contribution to within-industry allocational efficiency, as $M_{Ws} \equiv Y_s/Y_s^*$ is equal to $(\sum_{i\in I_s} \frac{P_i Y_i}{P_s Y_s} T_i^{\sigma-1})^{\frac{1}{1-\sigma}}$. A scale wedge larger than one means that the plant is small relative to its size in the efficient allocation.

## 4. Application to the Chilean data

This section applies the decomposition to the data on Chilean manufacturing plants to quantify the contribution of changes in allocational efficiency to changes in the Solow residual. Before proceeding through the various specifications, there are several things to note.

First, measured misallocation is sensitive to the treatment of outliers, as these are the plants that would expand or contract most if resources were reallocated optimally. If these are the result of mismeasurement, the analysis will overstate the extent of misallocation. To help guard against measurement error, Hsieh and Klenow (2009) trim the top and bottom 1% outliers of both physical and revenue productivity. I take an alternative approach and Winsorize the top and bottom 1% of the distributions of capital and labor wedges in each year. This means, for example, that if a plant's capital wedge falls in the top 1% of the distribution in one year, its capital stock in that year is replaced so that its new capital wedge would be at the 99th percentile.[18] Section E.3 of the online appendix tests the sensitivity of the results to this particular threshold.

Second, the heart of the analysis compares changes in allocational efficiency to changes in the appropriate Solow residual. The measures of aggregate output and input used to construct the residual do not rely on the model.[19] However, the appropriate factor shares used in constructing that residual depend on the model and therefore vary across specifications, as discussed in Section 3.2.

Lastly, throughout the analysis, the elasticity of substitution $\sigma$ is set to 3.

### 4.1. Production parameters

Resources are misallocated if there are deviations between plants' optimal and efficient levels of capital or labor. Since deviations are not directly observable, the methodology relies on strong assumptions about the functional forms of production function and demand structure.

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[18] In a panel, trimming outliers would be problematic. If the top and bottom 1% each year were dropped, then measured misallocation would be volatile due to the artificial entry and exit of plants that were dropped in one year but not the next. Alternatively, if plants that fell in the top or bottom 1% in any single year were excluded entirely from the analysis, too many plants would be dropped, as among the Chilean plants this would include some of the largest plants that account for a large share of aggregate value added. Because this analysis Winsorizes rather than trims these outliers, the levels of output loss due to within-industry misallocation are not directly comparable to those computed by Hsieh and Klenow (2009).

[19] Changes in aggregate value added, $d\ln Y$, are constructed as follows: real output in an industry-year is the sum of nominal value added divided by the industry's output deflator. Changes in aggregate output are then computed using a Tornqvist approximation to a Divisia index. Labor services are computed as the sum of the number of blue-collar workers plus the number of white-collar workers, corrected for the fraction of the year the plant was open. The aggregate capital share used to compute the change in the Solow residual from year $t-1$ to year $t$ is $[\alpha^{**}(t) + \alpha^{**}(t-1)]/2$.

Without a priori knowledge of plants' production functions, it is unclear whether cross-sectional differences in observed factor intensities reflect distortions or heterogeneous technologies.[20] To deal with this issue, the analysis is conducted under two specifications.

#### 4.1.1. Plant-specific parameters

The first specification proceeds under the assumptions that all long-run differences in factor expenditure shares reflect differences in underlying technology rather than distortions. The panel structure of the data can be used to infer the production parameters of each plant. In particular, I assume that while a plant may face a distortion in a particular year, it is, on average, undistorted. To this end, I compute the parameters of a single plant's production function as follows: In each year, I compute the log of the ratio of nominal expenditure on capital to nominal expenditure on labor. Under the assumption that, for each plant, the median of this quantity over all the years that the plant is in the sample reflects an undistorted choice of inputs, the parameters of the production function can be backed out accordingly.[21]

#### 4.1.2. Industry-specific shares: U.S. shares

The second specification assumes that all plants within an industry have the same factor intensities, and that any differences in factor expenditures reflect distortions. To parameterize these, I assume factor intensities are the same as those of the corresponding U.S. industries and that these U.S. industries are, on average, undistorted.[22] I use expenditure data from the NBER-CES Manufacturing Industry Database to compute the cost shares for the relevant industries in the U.S. for 1985.[23]

### 4.2. Reduced-form measures of misallocation

This section presents several commonly used reduced-form measures of misallocation. The figures below show the evolution of the dispersion of capital and labor wedges. Fig. 4 shows how the distribution of capital and labor wedges evolved over time using two measures of dispersion: the respective log deviations between the 90th and 10th percentiles and the 75th and 25th percentiles in the distribution among the balanced sub-sample of plants in the survey through 1988. The solid lines show the measures of dispersion of capital wedges. In each specification, there is a slight uptick in the 90–10 ratio from 1981 to 1982. These changes are small relative to the overall trend, and it is difficult to detect any movement in the 75–25 ratio. There is also a clear downward trend over time in the dispersion of capital wedges. It is tempting to interpret this as a gradual improvement in the efficiency of the allocation of resources. However, given how initial capital stocks are constructed, another explanation is that measurement error for capital variables is particularly large early in the sample. Finally, the dashed lines show dispersion in log labor wedges. While dispersion is rising from 1981 to 1982, 1982 does not stand out as an outlier.

Fig. 5 shows how scale wedges vary with plant size and how this changed during the crisis. Plants are divided into twenty groups in order of value added in 1981. The figure then plots the average of the log scale wedge for each group in 1981 and in 1982. Two patterns are clear. First, on average, larger plants have higher scale wedges. This means that in the efficient allocation, these plants would be even larger. This is a common feature of plant-level data, perhaps because larger plants have more market power and find it optimal to restrict output. Second, the distribution of scale wedges appears more flat in 1982, potentially pointing to less misallocation.

While these reduced-form measures of misallocation are not conclusive, they give little indication that the large decline in measured total factor productivity during the crisis was caused by increased within-industry misallocation.

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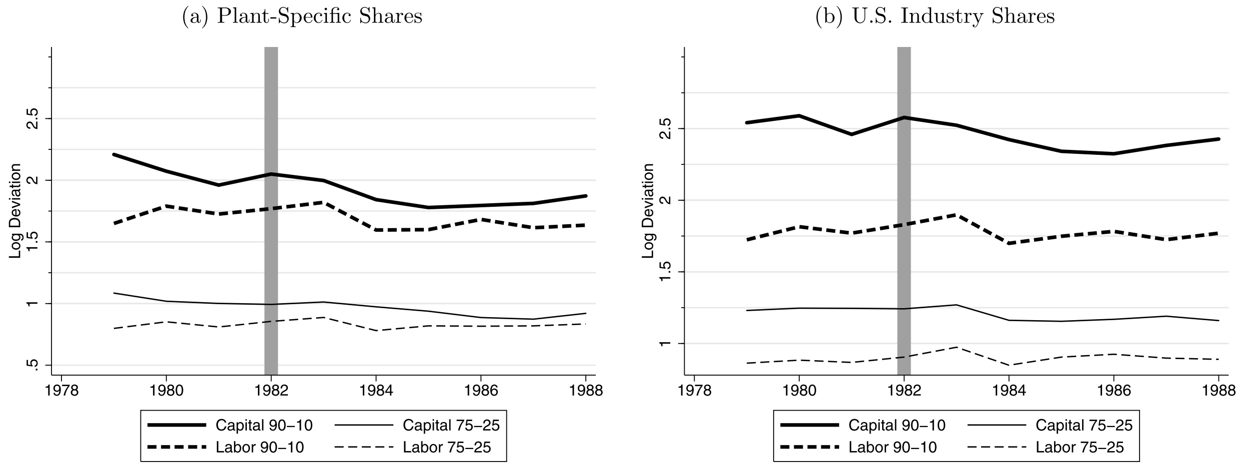
[20] An alternative is that each plant produces with a CES production function with capital and labor augmenting productivity. Using data on U.S. plants, Raval (2012) provides strong evidence of an elasticity of substitution less than one at the plant level. However, one cannot separately identify both the wedges and the productivity parameters, because there are more parameters than observables.

[21] The nominal expenditure on capital is computed as follows. For each type of capital, a nominal rental payment is imputed using the respective deflator, depreciation rate, and a real interest rate of 8%. The cost of capital is the sum of reported rental payments plus imputed rental payments for each type of capital.

This uses two simplifications. First, if actual real interest rates were used (with expected inflation measured as either ex-post inflation or using a simple forecast based on lagged inflation – see Section A of the online appendix), then the implied rental price would be much more volatile than aggregate rental payments around the time of the crisis. Second, the user cost of capital depends on the expected change in the price of capital. I have no way to directly measure expected changes in the price of capital, though capital price deflators show large swings in the prices of buildings, machinery, and vehicles during the contraction. If these changes are expected, there would be massive and unrealistic swings in capital's share of revenue; for some years, the user cost of certain types of capital would be negative. While this is not a completely innocuous simplification, the measures of user cost of capital implicitly assume that all changes in real capital prices are unexpected.

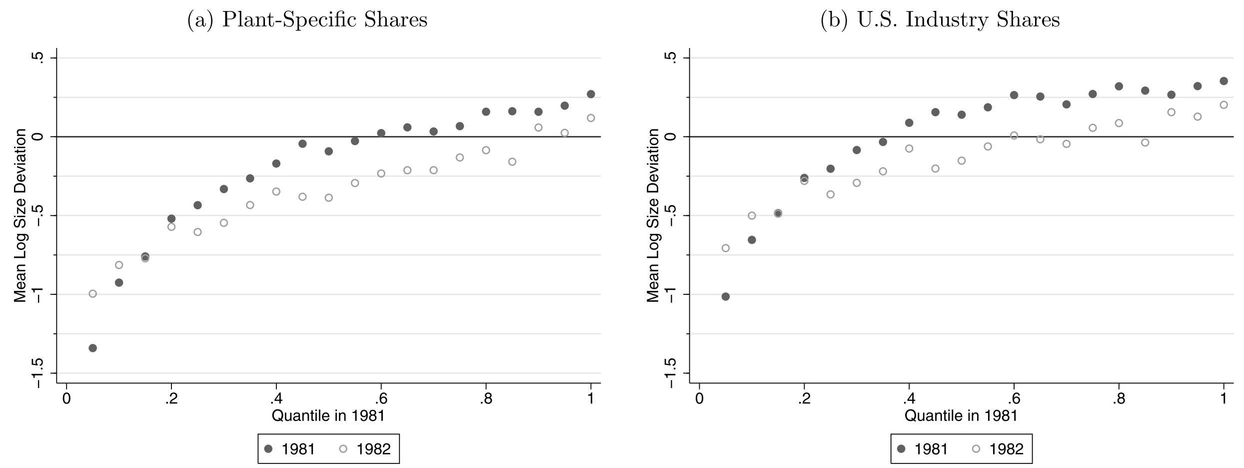
[22] It is possible that Chilean plants use different production processes than plants in the U.S. See Section E.1 of the online appendix for an alternative that uses Chilean industry shares, under the assumption that these are, on average, undistorted.

[23] The industry definitions used in the Chilean data are ISIC revision 2, while the industries in the NBER-CES Manufacturing Industry Database are usSIC1987. To reconcile the two, I use concordance tables that convert ISIC rev2 to ISIC rev3 and that convert usSIC1987 to ISIC rev3. I then match Chilean and U.S. industries if they get matched to a common ISIC rev3 industry.




*Note*: For each year, this figure shows a measure of dispersion of capital and labor wedges, the log deviations between the 90th and 10th percentiles and between the 75th and 25th percentiles of the respective distributions among plants in the sample from 1979–1988. The capital and labor wedges for plant $i$ are $\frac{P_iY_i/K_i}{P_i^*Y_i^*/K_i^*}$ and $\frac{P_iY_i/L_i}{P_i^*Y_i^*/L_i^*}$, where $K_i^*$, $L_i^*$ and $P_i^*Y_i^*$ are $i$'s capital, labor, and value added in the efficient allocation.

**Fig. 4.** Dispersion of capital and labor wedges.



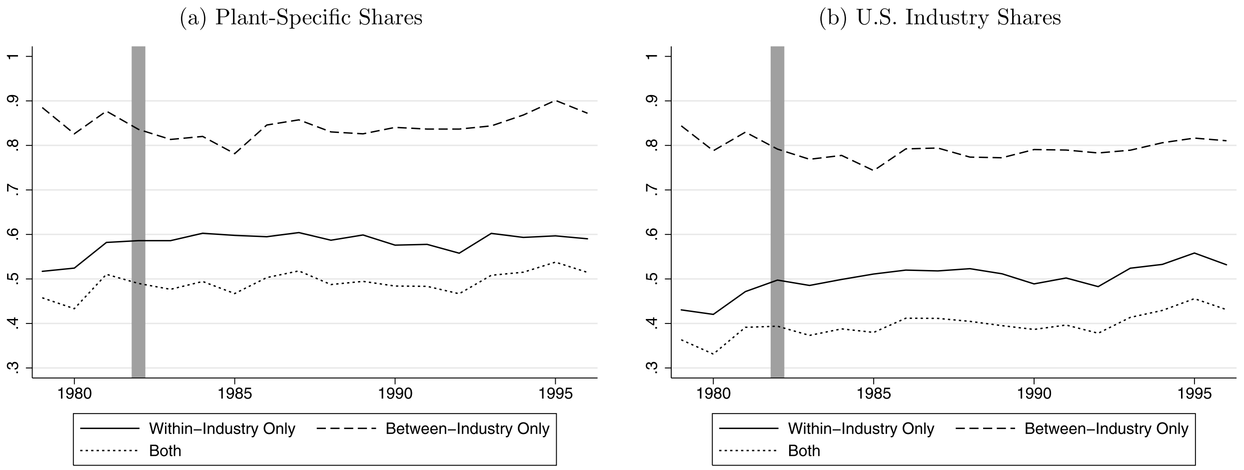

*Note*: Plants are divided into bins based on value added in 1981. This figure plots the average log scale wedge for each group in 1981 and 1982. A plant that was no longer in the survey in 1982 is not included in the 1982 average. The scale wedge for plant $i$ is $\frac{P_iY_i/(K_i^{\alpha_i}L_i^{1-\alpha_i})}{P_i^*Y_i^*/(K_i^{*\alpha_i}L_i^{*1-\alpha_i})}$, where $K_i^*$, $L_i^*$, and $P_i^*Y_i^*$ are $i$'s capital, labor, and value added in the efficient allocation.

**Fig. 5.** Scale wedges.

### *4.3. The contribution of allocational efficiency*

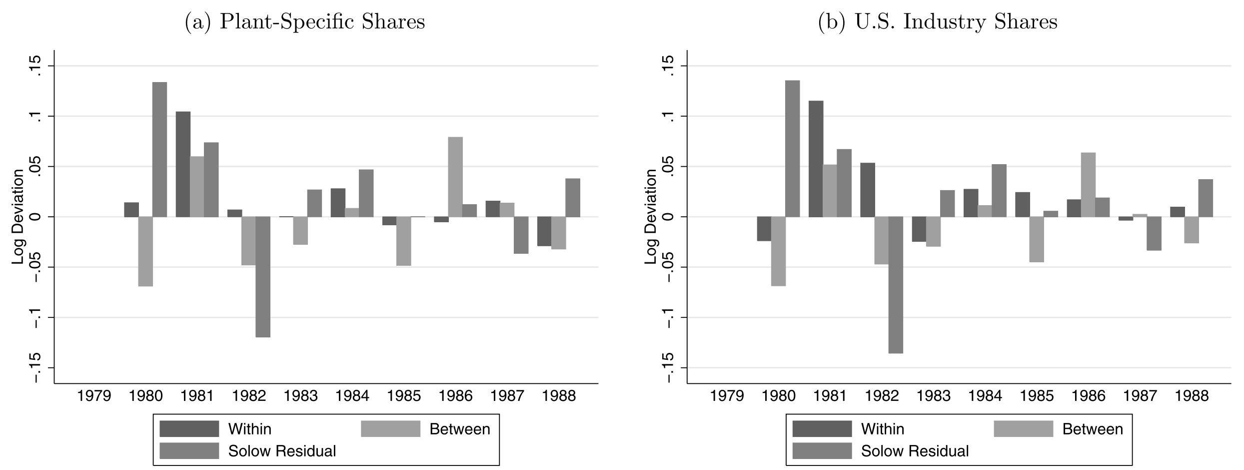
Even though the findings in the previous section hint at a small role of within-industry misallocation during the crisis, they are not sufficient to determine the impact of the allocational efficiency on output. For that, I turn to the structural decomposition.

Fig. 6 shows the level of allocational efficiency, measured as actual output relative to that of the frictionless optimum. In each graph, there are three lines. The solid line shows $M_W$, within-industry allocational efficiency. For example, in 1982, output is reduced to 58.6% of what it could be if factors were reallocated optimally within each industry in the specification using plant-specific shares. This corresponds conceptually to the metric of Hsieh and Klenow (2009); if capital and labor were reallocated optimally within industries, the percentage increase in aggregate value added would be $M_W^{-1} - 1$. The dotted line shows $M_B M_W$, the combined impact of within- and between-industry allocational efficiency; in 1982, output is reduced to 49.0% of the efficient optimum in which output could be reallocated both within and across industries. The dashed line is simply $M_B$, between-industry allocational efficiency. The exact values are listed in Section D of the online appendix.




*Note*: This figure shows the evolution of allocational efficiency over time. The line labeled "Within-Industry Only" shows $M_W$, actual output divided the output that could be attained if resources were allocated optimally within each industry. The line labeled "Between-Industry Only" shows $M_B$, the ratio of the output that could be attained if resources were allocated optimally within each industry and across all plants, respectively. The line labeled "Both" shows $M_W M_B$, actual output divided by the output that could be attained if resources were allocated across all plants.

**Fig. 6.** Allocational efficiency.




*Note*: This figure shows changes in allocational efficiency. Each year, the figure shows the log deviation of within-industry allocational efficiency, $M_W$, the log deviation of between-industry allocational efficiency, $M_B$, and the log deviation of the appropriate Solow residual.

**Fig. 7.** Contributions to changes in the Solow residual.

Note that with U.S. industry shares, output is farther from the efficient optimum. This is natural because more of the variation in factor expenditures is attributed to misallocation. For this analysis, however, *changes* in allocational efficiency are more relevant than the level.

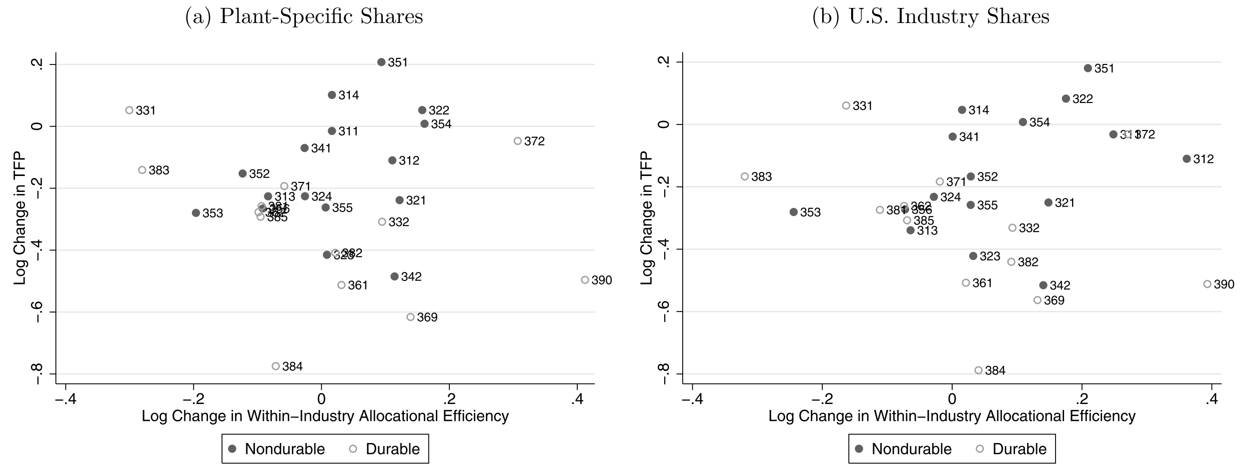
Fig. 7 shows the decomposition of changes in the appropriate Solow residual. Each year, three bars are plotted: the log deviation of within-industry allocational efficiency, $d\ln M_W$; the log deviation of between-industry allocational efficiency, $d\ln M_B$; and the appropriate Solow residual, $d\ln Y - \alpha_K^{**} d\ln K - (1-\alpha^{**}) d\ln L$. If the first two add up to the third, then the change in measured aggregate productivity is completely explained by the changes in the extent of misallocation. The changes in allocational efficiency in 1982 are summarized in Table 1. In both specifications, the contribution of between-industry allocational efficiency accounts for roughly one-third of the decline in the Solow residual in 1982. In contrast, changes of within-industry allocational efficiency do not help explain the decline. With plant-specific shares, within-industry allocational efficiency makes a slight positive contribution to growth in 1982. With U.S. industry shares, the within-industry contribution is positive and large enough to offset the between-industry contribution.

Interestingly, given the increase in TFP from 1982 to 1983, changes in allocational efficiency account for more than half of the cumulative change in the Solow residual from 1981 to 1983, although the timing of the changes does not fit well. In both specifications, the between-industry contribution plays a large role, while the within-industry contribution plays almost no role.

**Table 1**
Contribution of allocational efficiency to measured TFP in 1982.

| | Plant specific shares | U.S. industry shares |
|---|---|---|
| Within sectors | 0.007 | 0.053 |
| Between sectors | −0.048 | −0.047 |
| Other | −0.078 | −0.142 |
| Measured TFP (total) | −0.120 | −0.136 |

*Note*: For each specification, this table shows the log deviation of within-industry allocational efficiency, $d\ln M_W$, the log deviation of between-industry allocational efficiency, $d\ln M_B$, and the log deviation of the appropriate Solow residual for 1982. Other is the residual.




*Note*: This figure plots the log deviation of an industry's measured TFP in 1982 against the log deviation of within-industry allocational efficiency, $d\ln M_{Ws}$. Measured TFP for each industry is computed using the factor share $\alpha_s^*$.

**Fig. 8.** Industry TFP and within-industry efficiency in 1982.

*4.3.1. Alternative specifications*

The online appendix contains a variety of other specifications. Section E.1 uses an alternative specification of production functions, using industry-specific factor shares based on Chilean rather than U.S. industries. The results closely match the specification that uses U.S. industry shares.

Section E.2 conducts the same exercise, but restricts the sample to the balanced panel of plants that are in the sample every year from 1979 to 1988. The results are similar to those from the baseline specifications, suggesting that entry and exit were not the driving factor behind changes in either allocational efficiency or measured TFP.

Lastly, Section E.3 examines alternative thresholds for Winsorization. As one might expect, using the raw data magnifies the changes in within-industry allocational efficiency, and the series becomes much more volatile. Alternatively, Winsorizing the top and bottom 3% yields smaller changes in allocational efficiency. In either case, the between-industry measures of allocational efficiency are similar to the baseline quantitatively, and within-industry allocational efficiency follows the same qualitative pattern as the baseline, making a positive contribution to measured TFP.

## 5. Industry outcomes

During the crisis, measured TFP fell for the manufacturing sector as a whole because the decline of value added was much larger than the declines in capital and labor. Across individual industries, the patterns are similar. Changes in capital and labor were small relative to changes in value added so that variation in measured TFP closely tracks changes in value added.

Fig. 8 shows the changes in measured TFP and within-industry allocational efficiency for each industry in 1982. Across industries, there is a tremendous amount of variation in outcomes during the crisis. This variation can be used to assess the importance of various mechanisms that might have played a role during the crisis. In particular, this section studies two salient features of financial crises, declines in demand and deteriorating financial conditions.

**Table 2**
Industry summary statistics.

| | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Financial dependence | 0.244 | 0.220 | 0.336 | −0.450 | 1.140 |
| Export share | 0.098 | 0.064 | 0.103 | 0.009 | 0.360 |
| Import share | 0.152 | 0.121 | 0.113 | 0.015 | 0.418 |
| Materials share | 0.670 | 0.661 | 0.107 | 0.473 | 0.907 |
| Observations | 29 | | | | |

*Note*: Export share is the average from 1990 to 1996 of an industry's total exports as a fraction gross revenue. Financial dependence is the ratio of external finance to capital expenditures in the corresponding U.S. industry, constructed by Rajan and Zingales (1998). Import Share and Materials Share are averages over 1981–1982 of an industry's expenditure on imported raw materials and total materials as respective fractions of gross expenditures.

### *5.1. Industry TFP*

Assuming constant returns to scale, a reduction in demand should have no impact on true TFP. However, even with constant returns to scale, when adjusting capital and labor is costly, a plant's measured productivity may fall if it uses these inputs at less than full capacity.[24]

Demand for durables is typically more cyclically sensitive than demand for nondurables. Consequently, we would expect larger reductions in demand for plants that produce durable goods during the crisis. Fig. 8 shows that industries that produce durable goods also tended to have larger declines in measured TFP, consistent with a large role for adjustment costs.

During the crisis, total exports were fairly stable while domestic sales declined, consistent with a large reduction in domestic demand. Hence, plants that derive a larger fraction of revenue from the domestic market would be expected to experience larger declines in demand.

A second feature of the crisis was deteriorating financial conditions, which could impact measured productivity in a number of ways. One channel is that some subset of intermediate inputs require working capital or trade credit. Mendoza and Yue (2012) emphasize a working capital constraint for imported inputs, while in Pratap and Urrutia (2012), working capital is required for domestic intermediates as well. An increase in the shadow cost of working capital because external credit is either expensive or unavailable would raise the shadow cost of these inputs. For the production of value added, such an increase in the shadow cost of intermediates has the same impact as a negative technology shock, provided the elasticity of substitution between materials and other factors of production is positive, reducing measured productivity.[25]

A second channel is that tightening financial constraints would affect within-industry allocational efficiency. Financial frictions might increase misallocation by slowing reallocation. An efficient allocation of resources requires that capital and labor be reallocated from plants with negative shocks to plants with positive shocks. If tighter financial constraints prevent the latter from expanding, reallocation would fall and allocational efficiency would decline.

One way to distinguish between these two channels is that an increased shadow cost of some inputs should have a larger impact when those inputs represent a larger cost share. Specifically, if the first channel is important, the relationship between dependence on external finance and declining measured TFP should be stronger in industries with a larger cost share of the relevant inputs.

To assess the importance of each of these mechanisms, I construct measures of the relevant factors at the industry level. As an indicator of the importance of dependence on external finance, I use the measures of Rajan and Zingales (1998). This strategy uses information from each industry's counterpart in the U.S. under the assumption that differences across industries reflect technological features of those industries.[26] I measure an industry's propensity to export as the average from 1990 to 1996 of the ratio of total exports to total revenue, as the Manufacturing Census began collecting data on plant exports only in 1990. The Census has better information on inputs. To measure the cost shares of total materials and of imported inputs, I use the average of the industry's expenditure shares for each in 1981 and 1982. Table 2 summarizes the variation across industries in each of these measures.

[24] A decline in demand for an entire industry may reduce allocational efficiency as well. If the decline is asymmetric across plants, measured misallocation would rise if reallocation of capital and labor did not match shifts in demand. A symmetric reduction in demand could also increase misallocation within industries, depending on the form of adjustment costs. As an extreme case, suppose that investment is fully irreversible. A plant's optimal scale depends on both its productivity and demand, and would adjust capital only once its actual scale falls sufficiently below its optimal scale. If there is a large, temporary, symmetric decline in demand for all plants in an industry, plants are much less likely to invest. As a result, compared to normal times, plants with positive idiosyncratic productivity (or demand) shocks are less likely to increase capital usage relative to those with negative shocks. This slower pace of adjustment would reduce within-industry allocational efficiency.

[25] In the absence of adjustment costs, this would not reduce the measures of allocational efficiency defined above ($M_W$ and $M_B$), as those account for misallocation of capital and labor but not of materials.

[26] To capture "the amount of desired investment that cannot be financed through internal cash flows generated by the same business," Rajan and Zingales (1998) define a firm's use of external finance as one minus the ratio of total cash flow from internal operations in the 1980s to total capital expenditures in the 1980s, computed using data from Compustat. The measure for an industry is the median among all firms in that industry. Rajan and Zingales (1998) report this for 27 of the 29 industries studied here. The exceptions are 312 and 351, which together represented less than 4% of value added.

**Table 3**
Changes in industry TFP.

(a) Chile plant shares

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Durable | −0.075 | | | | | −0.122 | −0.148* | −0.118* |
| | (0.102) | | | | | (0.072) | (0.077) | (0.063) |
| Export share | | 0.755*** | | | | 1.101*** | 0.729** | 0.827*** |
| | | (0.227) | | | | (0.347) | (0.271) | (0.274) |
| Financial dependence | | | −0.265** | | 0.108 | 0.509 | 0.802 | −0.742 |
| | | | (0.111) | | (0.350) | (0.305) | (1.638) | (1.081) |
| Import share | | | | −0.193 | −0.085 | 0.516 | | 0.417 |
| | | | | (0.369) | (0.298) | (0.395) | | (0.424) |
| Fin dep × import | | | | | −1.924 | −3.277** | | −4.836*** |
| | | | | | (1.657) | (1.462) | | (1.636) |
| Materials share | | | | | | | 0.521 | 0.385 |
| | | | | | | | (0.459) | (0.398) |
| Fin dep × materials | | | | | | | −1.353 | 2.490 |
| | | | | | | | (2.547) | (1.714) |
| Observations | 29 | 29 | 27 | 29 | 27 | 27 | 27 | 27 |
| $R^2$ | 0.035 | 0.246 | 0.103 | 0.014 | 0.170 | 0.520 | 0.449 | 0.618 |

(b) U.S. industry shares

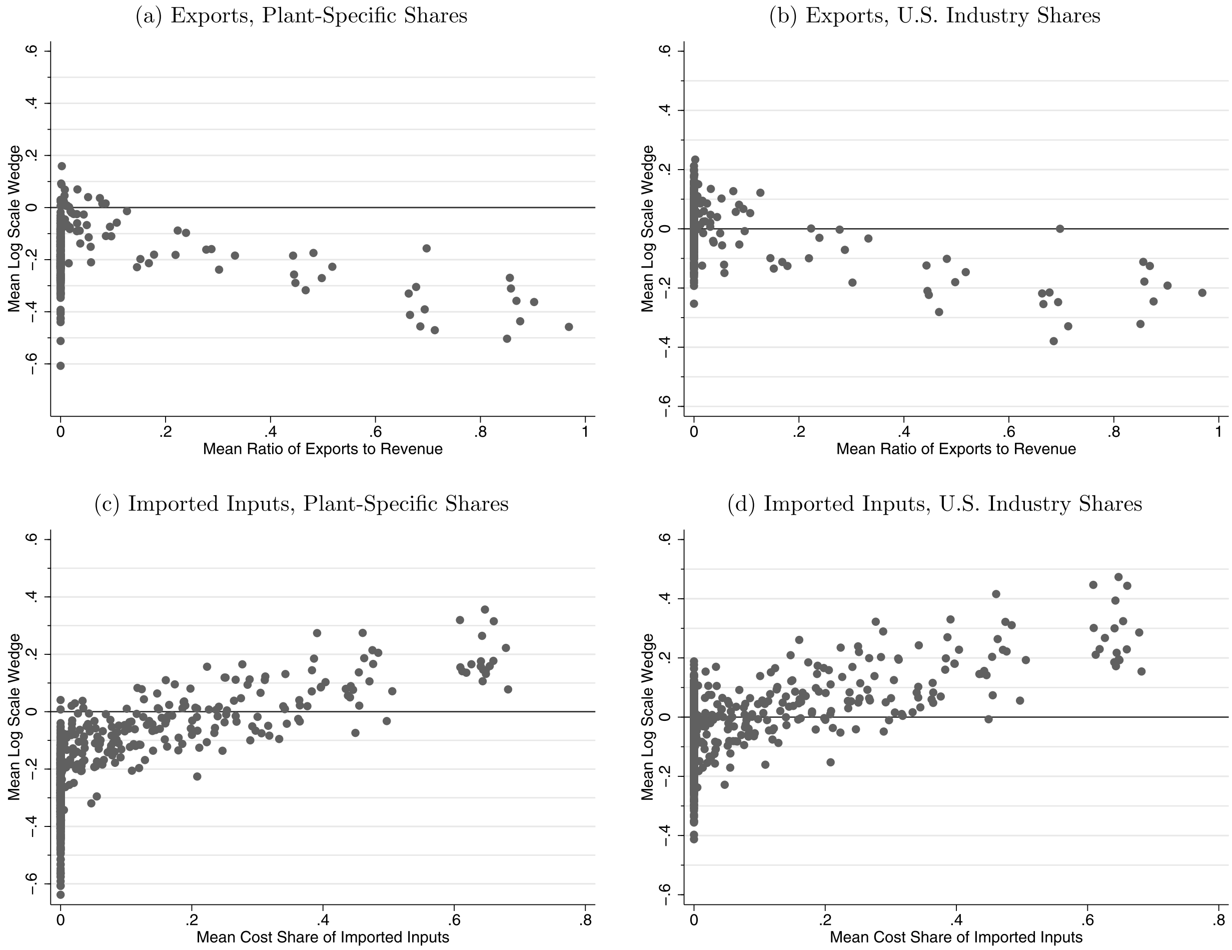
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Durable | −0.048 | | | | | −0.097 | −0.126* | −0.089 |
| | (0.106) | | | | | (0.071) | (0.072) | (0.068) |
| Export share | | 0.853*** | | | | 1.218*** | 0.820*** | 0.991*** |
| | | (0.207) | | | | (0.308) | (0.235) | (0.303) |
| Financial dependence | | | −0.255** | | 0.038 | 0.495 | 0.680 | −0.858 |
| | | | (0.104) | | (0.376) | (0.307) | (1.539) | (1.033) |
| Import share | | | | −0.216 | −0.145 | 0.584 | | 0.525 |
| | | | | (0.373) | (0.319) | (0.397) | | (0.478) |
| Fin dep × import | | | | | −1.528 | −3.106* | | −4.633** |
| | | | | | (1.748) | (1.505) | | (1.731) |
| Materials share | | | | | | | 0.480 | 0.286 |
| | | | | | | | (0.394) | (0.388) |
| Fin dep × materials | | | | | | | −1.153 | 2.615 |
| | | | | | | | (2.404) | (1.684) |
| Observations | 29 | 29 | 27 | 29 | 27 | 27 | 27 | 27 |
| $R^2$ | 0.014 | 0.304 | 0.092 | 0.017 | 0.146 | 0.528 | 0.458 | 0.605 |

*Note*: Robust standard errors in parentheses. Each column shows a regression of the log deviation of measured TFP from 1981 to 1982 on various industry characteristics. In each regression, industries are weighted by their average shares of value added in 1981 and 1982. Constant not shown.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3 shows how changes in industry TFP are related to these industry characteristics. Across specifications, exporting more is associated with smaller declines in TFP. Although less precise, point estimates indicate that producing durable goods is associated with larger declines in TFP. The coefficients on each are economically significant. A coefficient of −0.10 on the durables dummy indicates that nondurable industries experienced a 10 percentage point larger decline in measured TFP in 1982. A coefficient of 1 on export share implies that an industry whose exports represent 10 percentage points less of revenue had a 10 percentage point larger decline in measured TFP in 1982.

The results are also consistent with the story that deteriorating financial conditions increased the cost of working capital required to purchase imported inputs. As predicted, the coefficient on the interaction of financial dependence and cost share of imported intermediates is negative across all specifications, although without controlling for the export share, one cannot reject a coefficient of zero. Nevertheless, in all specifications the magnitude is economically significant; a coefficient of −2 indicates that a one standard deviation increase in financial dependence is associated with a 10.2 percentage point larger decline in measured TFP for an industry with the mean cost share of imported inputs than for an industry that does not import any intermediates.[27]

[27] With only 27 industries, estimating the coefficient on an interaction term slices the data thinly, so that the estimate hinges on relatively few industries. In addition, the measure of dependence on external finance is based on ratio of cash flow to capital expenditure, so the denominator is not ideal for this purpose.




*Note*: Panels (a) and (b) show the relationship between scale wedges and exports. In each year, plants are divided into fifty groups in order of ratio of exports to revenue. Each point shows the mean of log scale wedge and the mean ratio of exports to revenue for a single group in a single year. The figure shows all group-year observations from 1990 to 1996. Panels (c) and (d) show the relationship scale wedges and imported inputs. These are constructed in the same way, but use the cost share of imported inputs, and plot all group-year observations from 1979 to 1996.

**Fig. 9.** Scale wedges, exports, and imports.

### *5.2. Within-industry allocational efficiency*

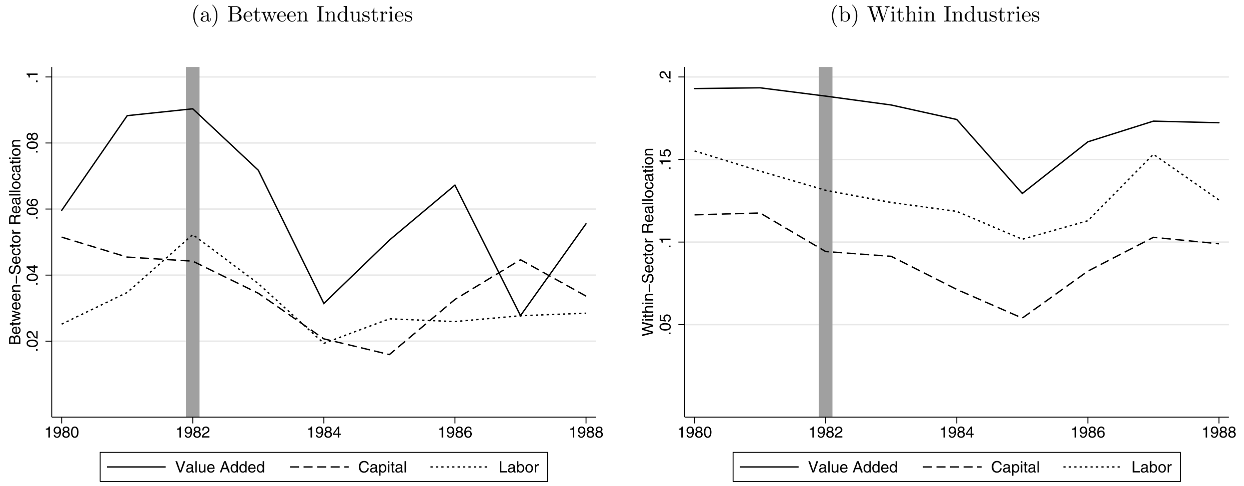
The decomposition in Section 4 indicated that within-industry allocational efficiency either remained constant or made a large positive contribution to measured TFP. This section shows how two factors discussed in Section 5.1, declining domestic demand and an increased shadow cost of imported goods, could have raised within-industry allocational efficiency.

Fig. 9 illustrates how scale wedges vary with exports and imports. Figs. 9(a) and 9(b) are constructed as follows. In each year for which export data are available, 1990–1996, plants are divided into fifty groups in order of export share of revenue. Each point in the figure plots the mean log scale wedge for a group against its mean export share of revenue. Figs. 9(c) and 9(d) use the same strategy, but use the cost share of imported inputs and all years in the period 1979–1996.

Figs. 9(a) and 9(b) show that plants that export more tend to have lower scale wedges.[28] This means that these plants' ratios of value added to capital and labor are relatively low. Suppose there is a reduction in domestic demand while foreign demand is unchanged and that it is costly to adjust capital and labor. While all plants would face reduced demand, the reduction would be smaller among plants that export. Thus, exporting plants' scale wedges would increase, as their ratios of value added to capital and labor would rise relative to those of plants that only sell domestically. Because exporting plants' scale wedges were initially low, this would raise allocational efficiency.

With an increased cost of imported inputs, the mechanism is similar. An increase in the cost of some intermediate inputs has the same impact on production of value added as a negative productivity shock. Figs. 9(c) and 9(d) show that plants

[28] This may seem surprising because large plants typically have larger scale wedges (see Fig. 5), and plants that export tend to be large. One possibility is that markups on exports are smaller than the average markup on domestic sales, as domestic markets may be less competitive.




*Note*: This figure shows the reallocation index for value added, capital, and labor. The between-industry index is the sum of the absolute value of changes in each industry's share. The within-industry measures are weighted averages of reallocation indices of each industry.

**Fig. 10.** Reallocation.

with a larger cost share of imported inputs typically have larger scale wedges. In response to an increased shadow cost of imported intermediates, value added would fall more for plants with a larger cost share of these inputs, lowering their scale wedges. Since these scale wedges were initially high, this would also raise allocational efficiency.

Section F of the online appendix contains the analog of Table 3, showing the association of changes in within-industry allocational efficiency with various industry characteristics. As predicted, the only factors that make a positive contribution to allocational efficiency are export share and the interaction of financial dependence with import share of cost. While the coefficients on each are fairly stable across specifications, precision varies; for most specifications, one cannot reject a coefficient of zero.

### 5.3. Reallocation and between-industry misallocation

In both specifications, deteriorating between-industry allocational efficiency accounted for roughly one-third of the decline in measured TFP in 1982. The decomposition is silent with respect to the causes of this deterioration. This section complements that analysis by examining changes in the pace of reallocation during the crisis.

Fig. 10 shows reallocation indices of value added, capital, and labor.[29] Fig. 10(a) shows a particularly large amount of reallocation of value added across industries in 1981 and 1982, much larger than the reallocation of capital and labor. This increase in reallocation of value added is natural, given industries' different exposure to the large shocks described in Section 5.1.

In contrast to reallocation of value added, reallocation of capital was only modestly above its long-run average. To see how this could reduce between-industry allocational efficiency, consider the following extreme example. Suppose two industries initially have the same value added, capital, and labor. Suppose also that, during the crisis, value added fell in the first industry but not the second, yet each industry's capital remained the same. Between-industry allocational efficiency would deteriorate as, in the efficient allocation, capital would be reallocated toward the (now) more marginally productive second industry. Thus, it seems the failure of reallocation of capital to keep up with other large changes exacerbated the decline in aggregate TFP.

Fig. 10(b) shows indices of within-industry reallocation for value added, capital, and labor within industries. All three exhibit a downward trend in the years surrounding the crisis, and reallocation of capital shows a slight dip in 1982. These are consistent with a modest slowing of the normal pace of reallocation of capital and labor.

[29] Following Kambourov (2009), the between-industry reallocation index for labor, for example, is defined as follows. Let $H_s(t)$ be total labor in industry $s$ at time $t$ as a fraction of total labor at $t$, so that $|H_s(t) - H_s(t-1)|$ is the absolute change in the share of labor in industry $s$ between $t-1$ and $t$. The reallocation index is defined as $I_B(t) \equiv \frac{1}{2}\sum_{s\in S}|H_s(t) - H_s(t-1)|$, the fraction of labor that was reallocated to a different industry. The within-industry allocation index constructs a similar index for reallocation across plants within each industry, $I_{Ws}(t)$. Then $I_W(t)$ is a weighted average of each industry's reallocation index, where an industry's weight is the average of its labor share in $t-1$ and $t$. Note that the weights used in computing this average differ across value added, capital, and labor. Using the same weights for all three series gives a similar picture.

**Table 4**
Contribution of capital utilization to measured TFP in 1982.

| | Plant specific shares | U.S. industry shares |
|---|---|---|
| Same for all plants | −0.035 | −0.046 |
| Same within industries | −0.053 | −0.068 |
| Different within industries | −0.059 | −0.076 |

*Note*: This table shows the contribution of capital utilization to measured TFP under three sets of assumptions. The first row assumes that all plants require the same energy per unit of capital. The second assumes that all plants within each industry require the same energy per unit of capital, but approximates around the same rate of utilization for each industry. The third row allows energy requirements to differ within industries and approximates around the same rate of utilization for all plants.

## 6. Capital utilization and labor hoarding

If it is costly to adjust capital or labor due to investment adjustment costs, specificity of capital, hiring and training costs, or institutional features such as firing restrictions, then plants may use other margins to change the scale of production. For example, a plant might use its capital less intensively, hoping to keep it from depreciating, or hoard workers but ask them to work fewer hours or exert less effort. Lower factor utilization would reduce measured TFP, as that measure would overstate effective inputs used in production.[30]

A common method of adjusting TFP for capital utilization is to use energy consumption as a proxy for capital services used.[31] Suppose that plant $i$ can produce with the production function $Y_i = A_i \hat{K}_i^{\alpha_i} L_i^{1-\alpha_i}$, where $\hat{K}_i = \min\{E_i/b_i, u_i K_i\}$ is effective capital services, $E_i$ is energy usage, $u_i \in [0,1]$ is utilization, and $b_i$ is the energy required to operate one unit of capital. A corrected Solow residual that accounts for capital utilization would use capital services rather than the stock of capital: $d\ln Y - \alpha d\ln \hat{K} - (1-\alpha) d\ln L$. Thus, the conventionally measured Solow residual would contain the extra term $\alpha(d\ln \hat{K} - d\ln K)$ that can be attributed to a change in capital utilization.

As with capital intensity, there are long-run differences across plants in energy usage per unit of capital. In constructing an empirical counterpart to aggregate capital services, a crucial factor is whether these differences reflect different energy requirements per unit of capital, $b_i$, or different rates of utilization, $u_i$.

Table 4 shows measures of the contribution of utilization to measured TFP, reflecting alternative sets of assumptions. First, if all plants have the same energy requirements per unit of capital (for each plant, $b_i = b$), then the change in aggregate capital services used is equal to the change in aggregate energy usage, $d\ln \hat{K} = d\ln E$. Studies that measure utilization using aggregate data often rely on such an assumption.

The second row uses the assumptions that energy requirements per unit of capital are the same for all plants within each industry (for each plant in industry $s$, $b_i = b_s$), but that long-run utilization rates are the same across industries. In this case, a first-order approximation of the change in aggregate capital services around uniform rates of utilization is a weighted average of the change in energy usage in each industry, $d\ln \hat{K} = \sum_{s\in S} \frac{\hat{K}_s}{\hat{K}} d\ln \hat{K}_s = \sum_{s\in S} \frac{K_s}{K} d\ln E_s$.

Lastly, the third row allows electricity requirements per unit of capital to vary by plant, but approximates around all plants having the same rate of utilization.[32]

For each set of assumptions, energy is measured as electricity usage (volume generated plus volume purchased minus volume sold).[33] In each year, I Winsorize the top and bottom 1% of the distribution of log deviations of each plant's ratio of electricity use to capital, $E_i/K_i$, from its median over all observations for that plant.

For each specification, the contribution to measured TFP is substantial. Comparing the first two rows shows that the interpretation of the heterogeneity in energy usage matters, as industries with a larger decline in utilization tended to use less electricity per unit of capital. In the interpretation that those industries require less energy per unit of capital, the contribution to the decline in measured TFP is larger than the aggregate change in energy usage would suggest.

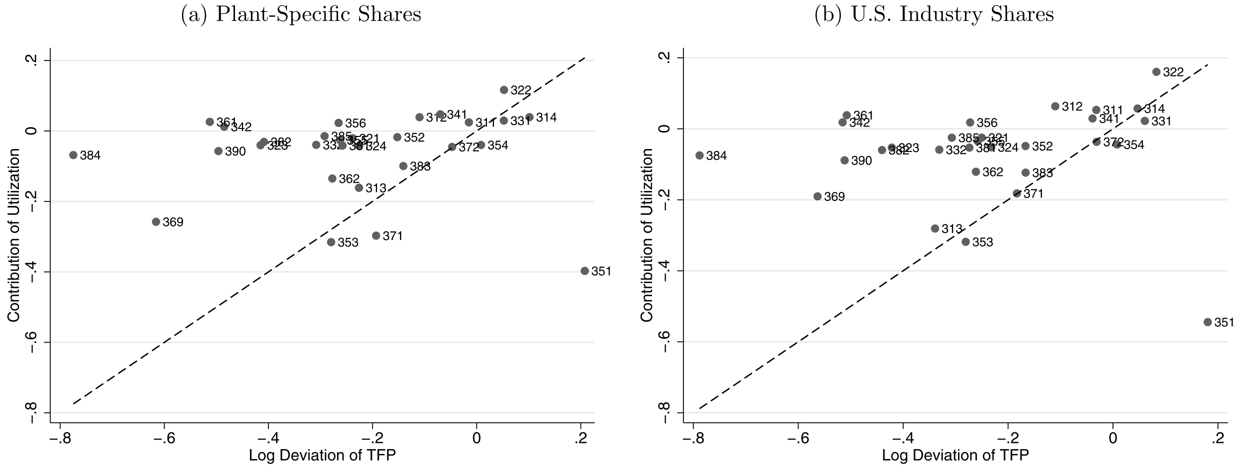
To illustrate the role of capital utilization, Fig. 11 plots the contribution from utilization against the change in the conventional Solow residual for each industry, along with the 45 degree line. The contribution is computed under the

30 Meza and Quintin (2007) argue that accounting for both capital utilization and labor hoarding is necessary to explain the decline in aggregate TFP during the Mexican crisis of 1994. Basu et al. (2006) argue that these represent an important component of measured TFP in the U.S. Among U.S. manufacturing industries, they estimate that the change in output due to changes in labor effort and capital utilization is 1.3 (durable manufacturing) and 2.1 (nondurable manufacturing) times the change in total hours in addition to the total change in hours. They do not separately identify the two channels.

31 See, for example, Burnside et al. (1995) and Burnside et al. (1996).

32 Accounting for capital services of entering and exiting plants complicates the expression as well. To be precise, I make the following calculations: Define $I^{\mathrm{Inc}}(t)$ to be the set of incumbents at $t$ – plants in the sample at both $t-1$ and $t$. For the intensive margin, I compute the usual Tornqvist approximation to a Divisia index. Let $d\ln \hat{K}^{\mathrm{Intensive}}(t) = \sum_{i\in I^{\mathrm{Inc}}(t)} \frac{1}{2}\left(\frac{K_i(t-1)}{\sum_{j\in I^{\mathrm{Inc}}(t)} K_j(t-1)} + \frac{K_i(t)}{\sum_{j\in I^{\mathrm{Inc}}(t)} K_j(t)}\right) \ln \frac{E_i(t)}{E_i(t-1)}$. For the extensive margin, I approximate the change in capital services with the change in actual capital. While this is not ideal, the share of capital accounted for by entering or exiting plants in any given year is small, on the order of 2%. Thus, the change in capital services is $d\ln \hat{K}^{\mathrm{Extensive}}(t) = \ln \frac{K^{\mathrm{Enter}}(t)}{K^{\mathrm{Exit}}(t-1)}$, where $K^{\mathrm{Enter}}(t)$ is capital used by plants that enter $t$ and $K^{\mathrm{Exit}}(t-1)$ capital used at $t-1$ by plants not in the survey at $t$ (note that these measures of capital account for the fraction of the year that these plants were in operation). Lastly, to get at the change in aggregate capital services used, I simply weight the two margins by their share of capital usage: $d\ln \hat{K}(t) = (1-\omega) d\ln \hat{K}^{\mathrm{Intensive}}(t) + \omega d\ln \hat{K}^{\mathrm{Extensive}}(t)$, where the share of capital accounted for by the extensive margin is $\omega \equiv \frac{1}{2}\left(\frac{K^{\mathrm{Exit}}(t-1)}{K(t-1)} + \frac{K^{\mathrm{Enter}}(t)}{K(t)}\right)$.

33 Using an index constructed by Greenstreet (2007) that combines real fuel and electricity usage gives quantitatively similar results.




*Note*: This figure compares changes in measured industry TFP with the contribution from capital utilization, along with a 45 degree line. This assumes that the change in capital services used in an industry is equal to the change in energy used, so that the contribution to conventionally measured TFP from capital utilization is $\alpha_s^*(d\ln E_s - d\ln K_s)$.

**Fig. 11.** Capital utilization and TFP.

second assumption, that all plants within each industry require the same energy per unit of capital: $\alpha_s^*(d\ln E_s - d\ln K_s)$. If the entire change in measured TFP were due to utilization, the industries would line up along the 45 degree line. In line with Table 4, the contribution of utilization for most industries is nontrivial but accounts for only a fraction of the decline in measured TFP.

Plants may also underutilize labor. To get at the contribution of labor hoarding during the crisis, a measure of average hours worked would be useful.[34] Using microdata from the Encuesta de Ocupacion y Desocupacion, a labor force survey of the greater Santiago area, I find that average weekly hours among those employed in the manufacturing sector fell from an average of 48.0 in 1981 to 46.1 in 1982. If the reduction in hours was symmetric across all plants, labor hoarding would account for 2.6 (plant-specific shares) or 2.2 (U.S. shares) percentage points of the decline in measured TFP.[35]

Weighted by labor quality, however, the decline in hours is smaller. Average weekly hours declined for almost all education groups, but not for those who attended university. Controlling for labor quality, the decline in hours is 2.8%.[36] This implies that labor hoarding contributed 1.8 (plant-specific shares) or 1.5 (U.S. shares) percentage points of the decline in measured TFP.

In summary, while these measures of utilization are fairly crude, they suggest that reduced factor utilization played a substantial role in the decline of measured TFP during the crisis.

## 7. Conclusion

During the Chilean crisis of 1982, the manufacturing sector experienced a dramatic fall in measured aggregate total factor productivity. To quantify the role of allocational efficiency, I develop a measures of allocational efficiency along the lines of Hsieh and Klenow (2009) and derive the appropriate measure of aggregate productivity to which these should be compared. Because this methodology relies heavily on functional-form assumptions, I use specifications that span two extremes: (i) plants have heterogeneous factor intensities even within the same industry and (ii) all plants in a industry have the same factor intensities.

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[34] The manufacturing census contains two measures of labor input: the number of workers and wage payments. To the extent that wage payments reflect hours worked and labor effort, differences in wage payments across plants in a cross section will capture differences in labor hoarding. However, changes in wage payments over time would conflate changes in the level of labor hoarding with changes in the wage level. While the measures of allocational efficiency only use information from the cross section (so that $M_W$ and $M_B$ would be valid), correcting TFP for labor hoarding requires knowing the change in the level of labor hoarding.

[35] The survey is conducted quarterly by the department of economics at the University of Chile. The March and June reports for 1981 and 1982 were available upon request at http://www.empleo.microdatos.cl/index.php. To arrive at these numbers, I computed the mean hours for each quarter using population weights provided with the data. For each year, I took a simple average across quarters. The contribution of labor hoarding is the labor share, $1-\alpha^{**}$, multiplied by the change in weekly hours. If, instead, the unweighted means from each survey were used, the contribution of labor hoarding would be 20–25 basis points larger.

[36] To control for labor quality, I constructed relative wages for six education categories by regressing log wages on these categories, controlling for time fixed effects, using all surveys in 1980–1990. Exponentiating the coefficient for each education category gives the relative wage for that group, which can be interpreted as (normalized) units of human capital. I then computed the change in log average hours for each group. The quality-weighted decline in hours is the weighted average of these changes, where each group's weight is the average of its 1981 and 1982 shares of human capital-hours.

Across specifications, I find that from 1981 to 1982 changes in between-industry allocational efficiency account for about one-third of the decline in measured TFP. In contrast, within-industry allocational efficiency either was roughly unchanged (plant-specific shares) or made a positive contribution large enough to offset the between-industry deterioration (common factor shares).

As with any study that measures allocational efficiency, it is difficult to attribute deviations from the frictionless optimum to a particular source. This is true in general, as deviations may stem from a variety of sources, but even more so in the years surrounding the crisis. There were many policy changes leading up to and in response to the recession, and identifying their individual effects is extremely difficult.

Nonetheless, variation in outcomes across industries points to several factors playing important roles, providing a broad outline of the crisis. Industries that were more sensitive to domestic demand saw larger reductions in industry TFP, pointing to a role for adjustment costs and reduced utilization. Consistent with this, I find that declining capital utilization can account for roughly 25–50% of the decline in measured aggregate TFP. In addition, I find suggestive evidence that deteriorating financial conditions raised the cost of working capital used to finance imported inputs.

Given industries' different exposure to these shocks, the decline in between-industry allocation efficiency reflects the relatively sluggish adjustment of capital and, to a lesser extent, labor, which failed to match the heightened pace of reallocation of value added across industries.

## Supplementary material

The online version of this article contains additional supplementary material.
Please visit http://dx.doi.org/10.1016/j.red.2012.10.005.

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