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Capital Misallocation: Cyclicality and Sources*

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Abstract

Capital misallocation can lower aggregate total factor productivity, but much less is known about its cyclicality. In this study, I use European firm-level data to establish that capital misallocation, as measured by the dispersion of capital returns, is higher during recessions and lower during booms. I also estimate that more than 50 percent of capital misallocation is due to variations between firms within industries. Furthermore, my results show that the net worth of medium-sized firms explains seven percent of the capital misallocation within industries and one-quarter of its cyclicality. This finding suggests financial frictions may play a role.

Keywords: Misallocation, Decomposition, Countercyclical, Net worth, Productivity

JEL classification: O11, O47, E32

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1 Introduction

Capital misallocation, the allocation of capital to plants with lower rather than higher capital returns, can lower aggregate total factor productivity (TFP), explaining a large part of cross-country TFP differences.[1] Although this relationship between capital misallocation and aggregate TFP has been well documented (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Bartelsman et al., 2013), the cyclicality of capital misallocation is much less studied (Bloom et al., 2018; Kehrig, 2015). This cyclicality is important because it may enhance the cyclicality of TFP. Identifying the sources and factors that account for capital misallocation and its cyclicality is also important for reducing TFP loss during recessions.

By using European firm-level data for 2005 to 2014, I establish that capital misallocation is countercyclical (i.e., higher during recessions and lower during booms). As for the sources of capital misallocation, I estimate that more than 50 percent is due to the variation between firms within industries and the remainder is divided between the variation among industries and the variation within firms over time. Furthermore, the results show that among medium-sized firms, net worth explains approximately seven percent of the capital misallocation within industries and around one-quarter of its cyclicality. This finding suggests that financial frictions may play a role.

To increase the number of observations, I use both the Amadeus and Orbis databases provided by Bureau van Dijk (BvD). I measure capital misallocation by the dispersion of the log marginal revenue product of capital (MRPK), as is standard in the literature. To show the cyclicality of capital misallocation, I calculate it for each year, separate out the cyclical components of both capital misallocation and gross domestic product (GDP), and then use those cyclical components in a business-cycle graph. In addition, to predict the degree of the association between the cyclical components of capital misallocation and GDP, I calculate the correlation between them.

On the business-cycle graph, my results show that in years in which the cyclical component of capital misallocation is high, the cyclical component of GDP is low. I also show a

[1] Hsieh and Klenow (2009) find that if the factors of production in China and India were to be reallocated to equalize returns to the extent found in the United States, then TFP would increase by 30 to 50 percent in China and 40 to 60 percent in India.

negative correlation between the cyclical components of both capital misallocation and GDP. Thus, both the business-cycle graphs and the correlations confirm that capital misallocation is countercyclical. The number of years covered by the Amadeus and Orbis databases for European countries is admittedly limited. To check the robustness of my result, therefore, I use the Compustat database, which has more than 50 years of data for publicly traded companies, for the United States and Canada. The results using the business-cycle graph and correlations using the Compustat database also confirm that capital misallocation is countercyclical.

To test the robustness of those results, I pool the estimated capital misallocation within industries for European countries to estimate the effect of the intensity of business cycles on capital misallocation. I measure the intensity of business cycles as the number of months in a recession for a given year. By using this measure, I establish that even at the industry level, capital misallocation is indeed countercyclical.

To understand the sources of capital misallocation, I decompose capital misallocation due to the variation between firms within industries, between industries, and within firms over time. I estimate that more than 50 percent of capital misallocation is due to the variation between firms within industries. Since the variation between firms within industries accounts for most of the capital misallocation, I focus on estimating the relative importance of several of the firm-level factors associated with capital misallocation. The results show that the net worth of firms can explain more capital misallocation than all the other examined firm-level factors (age of firms, number of employees, leverage ratio, input growth, and TFP shocks) combined. Overall, the net worth of medium-sized firms explains approximately seven percent of the capital misallocation within industries.

To show the firm-level factors associated with the cyclicality of capital misallocation, I consider only the net worth of medium-sized firms and compare the cyclical components of capital misallocation with and without controlling for the net worth of firms. The results show that the net worth of firms partly explains not only capital misallocation but also its cyclicality. To be more precise, the net worth of medium-sized firms, on average, explains around one-quarter of the cyclicality of capital misallocation.

My results support the analysis of Bernanke and Gertler (1989) on the role of borrowers' net worth on the business cycle. Owing to asymmetric information between lenders and borrowers, lenders tend to focus on net worth when making lending decisions (Bernanke and Gertler, 1989). The consequence is that firms with lower net worth may face a higher cost of borrowing and even tighter credit constraints during recessions than firms with higher net worth.

To identify industries that are highly susceptible to business cycles, I compare durable industries with non-durable industries and high external finance-dependent with low external finance-dependent industries. The results highlight that durable industries show a more cyclical pattern than non-durable industries and that industries relying heavily on external finance show a more cyclical pattern than those with a lower reliance.

Since the net worth of firms can explain more capital misallocation, I estimate the effect of net worth on MRPK. For all the sample countries, the results show a negative association between MRPK and net worth. For example, the average coefficient across all the sample countries is -0.27. That is, if net worth within firms increases by one percentage point over time, then one would expect MRPK to decrease by 27 percentage points. My results also show that the effect of net worth on MRPK varies more between firms within industries than between industries, confirming the aforementioned decomposition result.

This study relates to the literature on misallocation and financial friction. As mentioned, financial friction arises because of asymmetric information between lenders and borrowers (Bernanke and Gertler, 1989). Other research relevant to this study includes Banerjee and Duflo (2005), who discuss how capital misallocation can arise from credit constraints, as well as Midrigan and Xu (2014), Moll (2014), and Buera et al. (2011), who all show the association between financial friction and capital misallocation. Kehrig and Vincent (2017) find that credit-constrained firms rotate their funds from one set of plants to another set and that the resulting increase in the within-firm dispersion of MRPK is not a sign of misallocation. However, none of this literature focuses on the dynamic aspect of misallocation.

My research also contributes to the literature on the dynamics of misallocation. Gopinath et al. (2017) show that a decline in the real interest rate increases the MRPK dispersion across firms and that capital is misallocated toward firms that have higher net worth but are not necessarily more productive. Oberfield (2013), who examines the Chilean crisis of 1982, finds that a decline in between-industry allocational efficiency accounts for about one-third of the reduction in TFP. Sandleris and Wright (2014), who analyze the Argentina crisis of 2001, find that half of the decline in measured TFP can be accounted for by a deterioration in the allocation of resources. Ziebarth (2014) shows that capital misallocation increased during the Great Depression. Calligaris (2015) finds that misallocation has increased over time in Italy. Bloom et al. (2018) demonstrate that increases in the dispersion of plant-level productivity shocks are an important feature of recessions in the United States. Cooper and Schott (2015) and Kehrig (2015) document evidence that the dispersion of productivity is countercyclical. However, their result does not confirm that capital misallocation is countercyclical. Nonetheless, this study emphasizes the countercyclical pattern of capital misallocation across countries.

The remainder of this paper is organized as follows. Section 2 presents stylized facts on misallocation and productivity to provide an intuition about the importance of the cyclicality of capital misallocation. Section 3 describes the databases, data cleaning, and sample selection. It also includes the methods used to estimate MRPK and capital misallocation and to decompose MRPK variation. Section 4 explains my results. Section 5 concludes.

2 Misallocation and Productivity Facts

One of the purposes of this section is to show the correlation between net worth (a firm-level characteristic) and log MRPK. As mentioned in the Introduction, I measure capital misallocation by the dispersion of log MRPK, and the net worth of firms explains more MRPK variation than all the other examined firm-level characteristics combined. The second purpose of this section is to link, using the theoretical model proposed by Hsieh and Klenow (2009), misallocation to TFP. Although this is not the primary focus of my study, it does show that the MRPK variation that I measure is quantitatively important for economic growth and development. The third purpose of this section is to show the cyclicality of TFP. Although, again, this is not the focus of my study, it provides an intuition of the importance of the cyclicality of capital misallocation by suggesting its possible role in the cyclicality of TFP.

To adapt the theory of Hsieh and Klenow (2009) to the context of my research, I first determine the correlation between MRPK and the net worth of firms. To do this, I pool all observations and control for industry fixed effects. Figure 1, which is for Italy, depicts average log MRPK for each percentile of net worth. The figure shows a negative correlation between MRPK and net worth. I find similar results for all the sample countries (Figure 2). These results imply that firms with higher net worth have lower MRPK and that firms with lower net worth have higher MRPK.

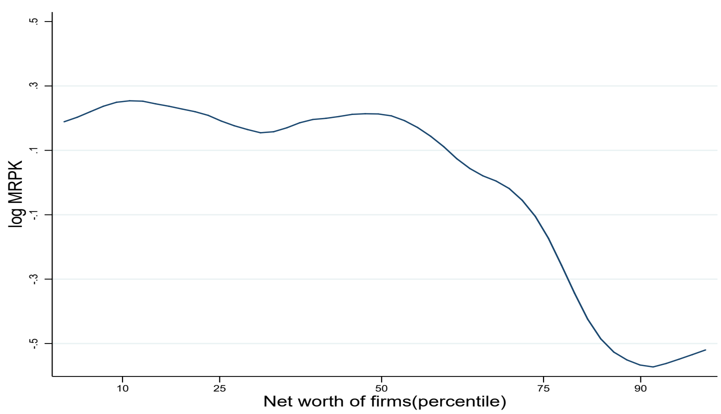
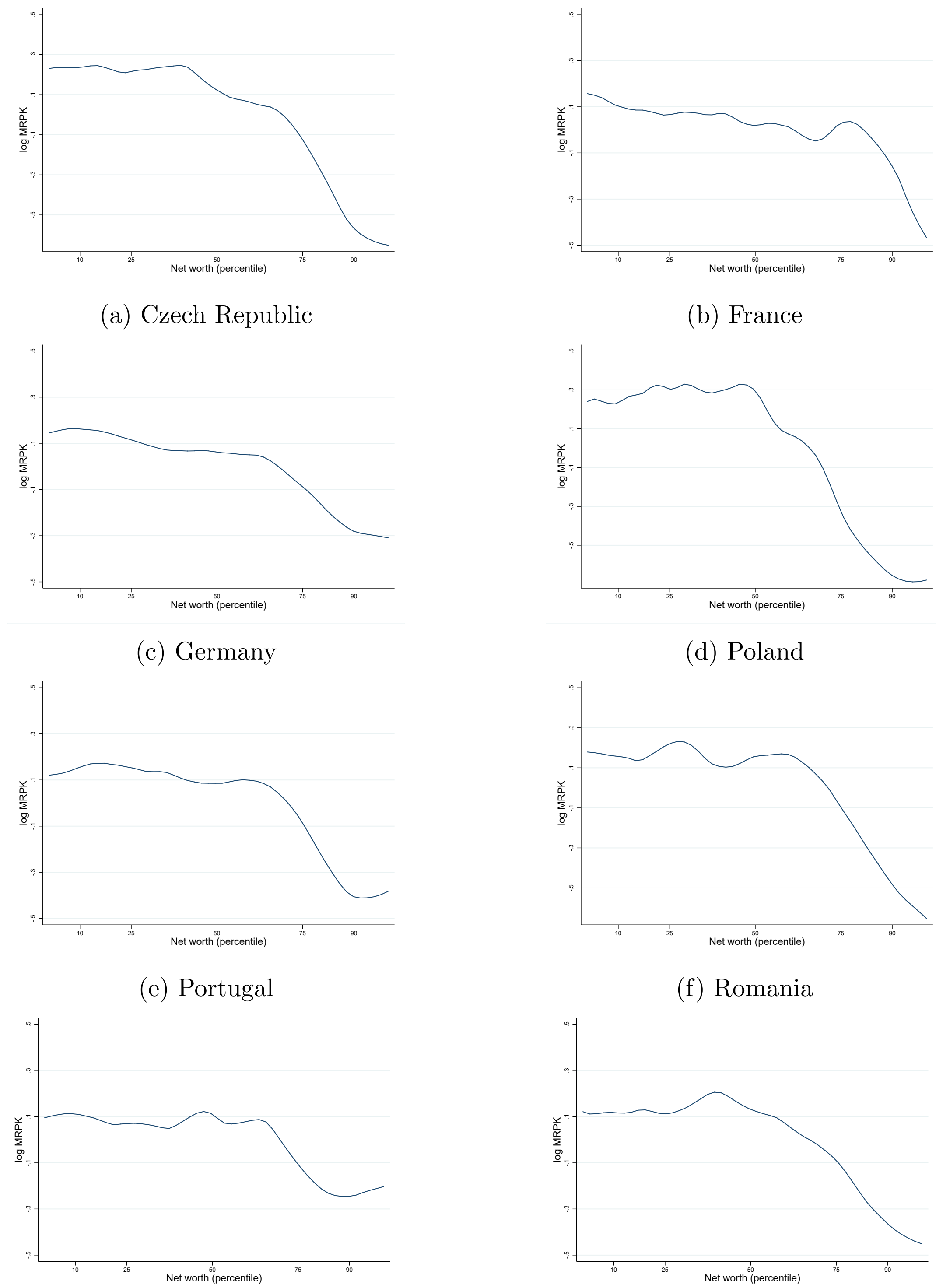


Figure 1: MRPK and net worth (Italy)

Note: This graph represents average log MRPK for each percentile of net worth. I pool all observations and control for industry fixed effects.

The negative correlation between MRPK and net worth could be due to the credit constraints arising from the asymmetric information between lenders and borrowers. Owing to this asymmetric information, lenders tend to focus on net worth when making lending decisions (Bernanke and Gertler, 1989). Therefore, firms with higher net worth may face a lower cost of borrowing than firms with lower net worth, even if they have the same productivity. Firms with higher net worth thus employ more capital and their MRPK is therefore low. In this way, the credit constraints arising from the asymmetric information between lenders and borrowers might lead to a dispersion in MRPK, or capital misallocation.



(a) Czech Republic
(b) France
(c) Germany
(d) Poland
(e) Portugal
(f) Romania
(g) Spain
(h) Sweden

Figure 2: MRPK and net worth

Note: This graph represents average log MRPK for each percentile of net worth. I pool all observations and control for industry fixed effects.

To show that MRPK variation matters, I use the theoretical model proposed by Hsieh and Klenow (2009) to link aggregate TFP to the resource misallocation that results from firm-level distortions. Instead of applying exogenous taxes to output and capital, I consider the distortions due to the credit constraints arising from the asymmetric information between lenders and borrowers. Appendix A explains the model with a detailed derivation. The profit maximization of firm i in industry s is given by

$$\max_{Y_{si},K_{si},L_{si},M_{si}} P_{si}Y_{si} - RK_{si} - wL_{si} - mM_{si} \tag{1}$$

subject to $Y_{si} = A_{si}K_{si}^{\alpha_K}L_{si}^{\alpha_L}M_{si}^{\alpha_M}$ and the credit constraints:[2]

$$\tau RK_{si} + wL_{si} + mM_{si} \leq W(z_{si}, \gamma), \quad \tau \geq 1 \tag{2}$$

where z_{si} is a firm characteristic (e.g., the net worth of firms), γ parametrizes the financial system (i.e., a better financial system allows you to borrow more against each dollar of collateral), and τ parametrizes the intensity of asymmetric information. $\tau = 1$ corresponds to perfect information. W is increasing in z_{si} (firms with higher net worth are less constrained) and γ (better financial systems are associated with higher values of γ). I use this form of credit constraint because it allows me to derive a result similar to that of Hsieh and Klenow (2009).

By using this form of credit constraint, the gap between aggregate efficient TFP, denoted as TFP^e, and the actual level of TFP can be expressed as

$$\frac{TFP}{TFP^e} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left(\frac{A_{si}}{\bar{A}_s} \cdot \frac{\overline{TFPR_s}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} \tag{3}$$

This equation implies that capital misallocation due to the credit constraints arising from the asymmetric information between lenders and borrowers can lower aggregate TFP.

This result has been well documented; however, no one has investigated the possible cyclicality of capital misallocation. One possible explanation for this cyclicality would be

[2] I follow the credit constraint formula from MIT OpenCourseWare; http://ocw.mit.edu.

that net worth is procyclical. Lenders' focus on net worth could create even tighter credit constraints during recessionary periods. For instance, Eurostat survey data show that the rate of rejection of bank loans was higher after the European financial crisis of 2008. Hence, the dispersion of MRPK—in other words, capital misallocation—could be higher during recessions and lower during booms, or countercyclical.

I predict that the cyclicality of TFP could be partly due to the cyclicality of capital misallocation. To show the cyclicality of TFP, I use TFP index data from the Penn World Table 9.0, 2016. To plot Figure 3, I calculate the average TFP index of all my sample countries. The results show that TFP fluctuates over time. All that remains is to show that this fluctuation in TFP is due in part to the cyclicality of capital misallocation. This will be the subject of future research.

Figure 3: Growth in TFP over time

Source: Penn World Table 9.0, 2016

Note: To plot this graph, I calculate the average TFP index for all my sample countries: Czech Republic, France, Germany, Italy, Poland, Portugal, Romania, Spain, and Sweden. I use $rtfpna$ data from the Penn World Table 9.0.

In summary, firms with higher net worth have lower MRPK and firms with lower net worth have higher MRPK. One possible explanation would be the credit constraints arising from the asymmetric information between lenders and borrowers. Credit constraints in turn could lead to capital misallocation and its cyclicality. The cyclicality of capital misallocation is important because it may enhance the cyclicality of TFP.

3 Methods

3.1 Data

In this paper, I employ various sources of data, which are listed in Table 1. As a primary database, to maximize the number of firms in the sample, I use both the Amadeus database[3] and the Orbis database[4] on European countries as recommended by Kalemli-Ozcan et al. (2015). I use the Amadeus database through Wharton Research Data Services.[5] Both databases are compiled by BvD, and they cover firms reporting to either the local tax authorities or data collection agencies. One advantage of this focus on European countries is that firm reporting is mandatory in Europe. I use nine countries: Czech Republic, France, Germany, Italy, Poland, Portugal, Romania, Spain, and Sweden. I consider these nine countries from European countries because they have sufficient data in those databases in my study period. Since challenges related to the estimation of the production function are less severe in the manufacturing sector than in other sectors, my analysis focuses on manufacturing industries.

I clean the data in five steps. First, I use only the unconsolidated account of firms for several reasons, the most important being to avoid including the total sales of a multinational across affiliates located in different countries. Second, I clean the data of basic reporting mistakes. In this step, I drop firms with negative values for the number of employees, operating revenue, the cost of employees, total assets, tangible fixed assets, and the cost of materials in any year. In addition, I drop firm-year observations with zero values or missing values for the number of employees, operating revenue, the cost of employees, tangible fixed assets, total assets, and the cost of materials. Furthermore, I drop firm-year observations with negative values for current liabilities, non-current liabilities, and shareholders' funds. Third, I winsorize observations below the first percentile or above the 99th percentile of the distribution for operating revenue, the cost of employees, tangible fixed assets, the cost of materials, and the net worth of firms. Finally, I drop the industry if the number of observations for given year is five or fewer.

[3] https://amadeus.bvdinfo.com/version-2015813/home.serv?product=amadeusneo.

[4] https://www.bvdinfo.com/en-gb/our-products/data/international/orbis.

[5] https://wrds-web.wharton.upenn.edu/wrds/.

After implementing this basic cleaning, I construct the variables for my analysis. I construct the age of firms by using the standard measure: the difference between the year of the balance sheet information and year of incorporation of the firm plus one. I drop observations with a reported year of incorporation that implies negative age values or missing values. I winsorize observations above the 99th percentile of the distribution for the age of firms. I winsorize the age of firms because outliers raise mean firm age. In addition, to construct the capital stock, I use tangible fixed assets. Furthermore, I construct net worth as the difference between total assets and total liabilities (the sum of current and non-current liabilities). Finally, to calculate the leverage ratio, I divide total fixed assets by shareholders' funds.

Table 1: Data sources

Data	**Data Source**	**Data Level**
European countries		
Primary database	Amadeus database	Firm level
Primary database	ORBIS database	Firm level
Deflators	Structural Analysis (STAN) database	SIC2
Exports, Imports, and Output	World Input Output Table database	NACE2
Nominal exchange rate	Penn World Table 9.0	Country level
TFP	Penn World Table 9.0	Country level
United States		
Primary database	Compustat database	Firm level
Deflators	NBER-CES	U.S. SIC4 1987
Total payroll	NBER-CES	U.S. SIC4 1987
Total value of shipments	NBER-CES	U.S. SIC4 1987
Total cost of materials	NBER-CES	U.S. SIC4 1987
Canada		
Primary database	Compustat database	Firm level
Deflators	Statistics Canada's KLEMS database	NAICS3 2007
Cost of capital services	Statistics Canada's KLEMS database	NAICS3 2007
Cost of labor input	Statistics Canada's KLEMS database	NAICS3 2007
Cost of materials input	Statistics Canada's KLEMS database	NAICS3 2007

To compute the trade share at a two-digit industry-level, I use the National Input Output Tables from the World Input Output Table (Timmer et al., 2015).[6] From these, I use exports, imports, and output at a two-digit industry level. To deflate tangible fixed assets, the cost of materials, and the net worth of firms, I use deflators from the STAN database from the Organization for Economic Co-operation and Development (OECD).[7] To convert all monetary values into the same currency, I use the exchange rate from the Penn World Table 9.0 (Feenstra et al., 2015).[8] To measure institutional quality, I use the World Bank Governance Indicators (Kaufmann and Kraay (2018)).[9] These indicators are voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption.

The number of years covered by the Amadeus and Orbis databases for European countries is admittedly limited. To test the robustness of my results, I use firm-level data from the Compustat database, which has more than 50 years of data, for the United States and Canada. I use the Compustat database through Wharton Research Data Services. I use sales, the capital stock (measured by *property, plant, and equipment - total (net)*), and industry classifications from this database. For sales and the capital stock, I use the deflators from the National Bureau of Economic Research (NBER) and the U.S. Census Bureau's Center for Economic Studies (CES) productivity database for the United States (Bartelsman and Gray, 1996) and Statistics Canada's KLEMS productivity database for Canada.[10]

For the United States, I use the 1987 SIC version of the NBER-CES productivity database (Becker et al., 2018).[11] To calculate the capital share for the United States, I use total payroll, the total value of shipments, and the total cost of materials at the four-digit SIC industry level (SIC4). To calculate the capital share for Canada, I use the cost of labor input, cost of capital services, and cost of materials input from Statistics Canada's KLEMS productivity database.

Since I use various data sources, the timeframe of this study is different for each country.

[6] `http://www.wiod.org/new\_site/home.htm`.

[7] For countries that are not part of the OECD, I use the calculated mean deflators of European OECD countries.

[8] DOI: 10.15141/S5J01T.

[9] `http://info.worldbank.org/governance/WGI/#home`.

[10] Statistics Canada's KLEMS productivity database is available upon request from the Economic Analysis Division of Statistics Canada.

[11] `http://www.nber.org/nberces/`.

Because web-based data from Amadeus and ORBIS for European countries are available for 10 years with two-year lags, the number of observations before 2005 and after 2014 is low. To cover the maximum number of observations in each year, therefore, I use data only for 2005 to 2014. For the United States, since the NBER-CES database is available up to 2011, I use the Compustat database for 1960 to 2011. Since Statistics Canada's KLEMS productivity database is available for 1961 to 2014, I use the database for 1961 to 2014 for Canada.

For the recession data on European countries, I use the OECD-based recession indicators.[12] Since Romania is not part of the OECD, I use the recession indicators for OECD Europe. I use the recession data from the NBER database for the United States[13] and the C.D. Howe Institute report for Canada (Cross and Bergevin, 2012).

After cleaning and merging the Amadeus and Orbis databases, Table 2 presents the number of observations for three groups of firms (i.e., surviving, exiting, and entering) in 2006 and 2014. The numbers of surviving firms for each country in 2006 and 2014 differ because I create the indicator variable for those groups before cleaning and dropping observations. For example, after cleaning the number of surviving firms for Italy in 2006, it is 13,980, whereas it is 33,572 in 2014. Creating this indicator variable for those groups before dropping or cleaning would remove false death and birth from my analysis.

Table 3 presents the summary statistics for all the countries in my dataset. Except for employment and the age of firms, all entries in the table are in millions of dollars. Operating revenue is deflated with gross output indices, the cost of employees is deflated with the consumer price index, the capital stock and net worth are deflated with gross fixed capital formation indices, and the cost of materials is deflated with intermediate input indices at the two-digit industry level with a base year of 2010 from the STAN database. For each year, I first calculate the means and standard deviations without weighting across all firms and industries. The entries in the table denote the means and standard deviations averaged across all the years in each country.

[12] `http://www.oecd.org/sdd/leading-indicators/oecdcompositeleadingindicatorsreferenceturningpointsandco` `htm`.

[13] `http://www.nber.org/cycles.html`.

Table 2: Number of firms in 2005 and 2014

Country	**2005**			**2014**		
	Surviving firms	Exiting firms	Total firms	Surviving firms	Entering firms	Total firms
Czech Republic	4139	2705	6844	4200	6657	10857
France	22968	37628	60596	22673	25491	48164
Germany	4196	5249	9445	1941	1488	3429
Italy	41843	44194	86037	37527	57021	94548
Poland	2411	1850	4261	3024	6718	9742
Portugal	6624	3451	10075	6250	15140	21390
Romania	13032	10252	23284	10664	9501	20165
Spain	34202	14967	49169	32256	20243	52499
Sweden	2845	3358	6203	2442	9391	11833

Note: Exiting, entering, and surviving columns represent the number of observations.

Table 3: Summary statistics of selected variables

Country	Sales	Employment	Wage Bill	Capital Stock	Cost of Materials	Net Worth	Age
Czech Republic	12.00	85.38	1.41	3.31	7.74	4.42	12.55
	111.12	258.10	6.66	25.90	89.81	40.70	5.88
France	10.56	44.21	1.79	1.37	5.10	2.82	18.13
	241.39	434.37	21.43	19.90	160.62	33.64	14.26
Germany	78.01	225.40	11.83	10.13	45.18	16.14	29.87
	713.30	678.51	51.77	55.66	598.98	102.25	32.67
Italy	7.72	31.75	1.13	1.75	4.06	2.32	17.73
	49.13	164.08	5.29	10.36	34.33	15.13	13.65
Poland	13.96	145.79	1.24	4.03	8.89	4.85	15.72
	86.21	339.89	4.12	29.67	64.81	37.66	15.57
Portugal	3.09	23.44	0.47	0.89	1.74	1.17	17.19
	23.78	60.98	2.01	6.58	17.08	8.55	13.30
Romania	2.69	45.59	0.33	1.19	1.58	1.12	11.15
	36.55	261.21	2.48	12.69	28.14	14.32	5.85
Spain	7.03	23.81	0.99	1.74	4.55	2.60	17.25
	132.46	129.10	6.43	24.40	117.02	23.16	10.89
Sweden	4.99	15.10	0.96	1.20	2.67	1.63	20.48
	39.93	64.68	4.76	16.66	24.39	18.96	14.96

Note: The entries in the table denote the unweighted means and standard deviations (second row for each country) averaged across all the years in each country.

3.2 Measurement of MRPK

To measure MRPK, I assume that firm i in industry s at time t produces output Y_{sit} by using the following Cobb–Douglas technology:

$$Y_{sit} = A_{sit} K_{sit}^{\alpha_K^s} L_{sit}^{\alpha_L^s} M_{sit}^{\alpha_M^s}, \quad \alpha_K^s + \alpha_L^s + \alpha_M^s = 1 \tag{4}$$

where K_{sit} is the capital input, L_{sit} is the labor input, and M_{sit} is materials. Furthermore, I assume that the production function and α's are industry-specific for a given country. A_{sit} is an idiosyncratic productivity component.

The firm sells its goods in a monopolistic product market, subject to an isoelastic downward-sloping demand curve:

$$Y_{sit} = B_{sit} P_{sit}^{-\sigma} \tag{5}$$

where B_{sit} is the demand shifter, P_{sit} denotes the output price for firm i for industry s in period t, and $-\sigma < -1$ is the demand elasticity.[14] For ease of measurement, I assume σ to be constant for all firms and industries. By using equation (5), I can derive the following demand function:

$$P_{sit} = \left(\frac{Y_{sit}}{B_{sit}}\right)^{-\frac{1}{\sigma}} \tag{6}$$

By combining equations (4) and (6), I can obtain the sales-generating production function:

$$\begin{aligned} S_{sit} &= P_{sit} Y_{sit} \\ &= \left(\frac{Y_{sit}}{B_{sit}}\right)^{-\frac{1}{\sigma}} Y_{sit} \\ &= B_{sit}^{\frac{1}{\sigma}} \left(A_{sit} K_{sit}^{\alpha_K^s} L_{sit}^{\alpha_L^s} M_{sit}^{\alpha_M^s}\right)^{1-\frac{1}{\sigma}} \\ &= \Omega_{sit} K_{sit}^{\beta_K^s} L_{sit}^{\beta_L^s} M_{sit}^{\beta_M^s} \end{aligned} \tag{7}$$

[14] To be explicit on the demand shifter, I could use a similar demand function to the specification of Hsieh and Klenow (2009): $P_{sit} = \lambda_s \frac{\sigma-1}{\sigma} Y_{sit}^{-\frac{1}{\sigma}}$.

where $\Omega_{sit} = B_{sit}^{\frac{1}{\sigma}} A_{sit}^{1-\frac{1}{\sigma}}$ and $\beta_X^s = \alpha_X^s(1 - \frac{1}{\sigma})$ for $X \in \{K, L, M\}$. In this study, I define productivity, or TFPR, as $\omega_{sit} \equiv ln(\Omega_{sit})$. By using the sales-generating production function, I can derive MRPK as follows:

$$MRPK_{sit} = log(\beta_K^s) + log(S_{sit}) - log(K_{sit}) \tag{8}$$

To estimate $MRPK_{sit}$, I first need to measure β_K^s. Following Asker et al. (2014), I use the sales-generating production function coefficients, which are equivalent to the share of the input's expenditure in sales, or formally

$$\beta_X^s = median\left(\left\{\frac{P_{sit}^X X_{sit}}{S_{sit}}\right\}\right), \; for \; X \in \{L, M\} \tag{9}$$

To recover the coefficient of capital, β_K^s, I assume constant returns to scale in production, $\alpha_K^s + \alpha_L^s + \alpha_M^s = 1$, such that

$$\beta_K^s = \frac{\sigma - 1}{\sigma} - \beta_L^s - \beta_M^s \tag{10}$$

To compute β_K^s, I follow Bloom (2009) and set the elasticity parameter, σ, to four. The sum of the labor (β_L^s) and materials (β_M^s) coefficients might exceed 0.75 for some industries, thus implying a negative capital coefficient. In these cases, I replace the negative capital coefficient with the country's average coefficient.

3.3 Linear Mixed Models

I estimate two linear mixed models: unconditional and conditional. I use the unconditional linear mixed model to decompose capital misallocation and the conditional linear mixed model to estimate the effect of net worth on MRPK. To estimate these models, I use the restricted maximum likelihood method. As this method takes into account the degrees of freedom of the fixed effects when estimating the variance components, its random effects estimates are less biased than the full maximum likelihood estimates.

To decompose capital misallocation into misallocation due to the variation between firms within industries, variation between industries, and variation within firms over time, I use the unconditional linear mixed model. Specifically, I estimate the variance components of MRPK due to those variations. This method is appropriate for estimating the variance components of MRPK compared with the ANOVA approach used in the traditional literature for two reasons. First, the group parameters in the ANOVA model, such as those related to industries, are often treated as fixed effects, which ignores the random variability associated with group-level characteristics. Second, the ANOVA method is insufficiently flexible to handle missing data or greatly unbalanced designs.

To explain the unconditional linear mixed model, I use the following standard regression model with fixed and random effects and without covariates:

$$MRPK_{sit} = \overbrace{\beta_{00}}^{Fixed} + \overbrace{\nu_{s0} + \eta_{si0} + \epsilon_{sit}}^{Random} \tag{11a}$$

$$\epsilon_{sit} \sim iid\ N(0, \sigma_\epsilon^2) \tag{11b}$$

$$\eta_{si0} \sim iid\ N(0, \sigma_\eta^2) \tag{11c}$$

$$\nu_{s0} \sim iid\ N(0, \sigma_\nu^2) \tag{11d}$$

$$Var(MRPK_{sit}) = \sigma^2 = \sigma_\nu^2 + \sigma_\eta^2 + \sigma_\epsilon^2 \tag{11e}$$

$$\rho_z = \frac{\sigma_z^2}{\sigma_\nu^2 + \sigma_\eta^2 + \sigma_\epsilon^2}, \quad z = \nu, \eta, \epsilon \tag{11f}$$

where $MRPK_{sit}$ is MRPK for industry s, firm i, and year t; β_{00} is the grand mean of MRPK; ν_{s0} is the random industry effect with a mean of zero and variance of σ_ν^2; η_{si0} is the random firm effect within industries with a mean of zero and variance of σ_η^2; ϵ_{sit} is the random year effect with a mean of zero and variance of σ_ϵ^2; and $\sigma^2 = \sigma_\nu^2 + \sigma_\eta^2 + \sigma_\epsilon^2$ is the total variance of these three random effects. To compute the proportion of the variance within firms over time (ρ_ϵ), between firms within industries (ρ_η), and between industries (ρ_ν), I use equation (11f):

Next, to explain the conditional linear mixed model, I include covariates in the unconditional linear mixed model to estimate the effect of net worth on MRPK. This model allows me to estimate the variability of the effect of net worth on MRPK due to the variation between firms within industries and variation between industries. Following the standard literature, I control for the input growth to remove the effect of growing firms and for the TFPR shocks to remove the effect of any adjustment costs. In addition, I control for the age effect and size (as measured by the number of employees) effect of firms within industries. I use the following standard regression model with fixed and random effects:

$$\begin{aligned}
MRPK_{tij} &= \overbrace{\beta_{00} + \beta_{10}A_{si} + \beta_{20}E_{si} + \beta_{01}N_{sit} + \pi_2 G_{sit} + \pi_3 S_{sit}}^{Fixed} \\
&+ \overbrace{\eta_{si0} + \eta_{si1}N_{sit} + \nu_{s0} + \nu_{s1}N_{sit} + \epsilon_{sit}}^{Random} && (12a) \\
\epsilon_{sit} &\sim iid\ N(0, \sigma_\epsilon^2) && (12b) \\
\begin{Bmatrix} \eta_{si0} \\ \eta_{si1} \end{Bmatrix} &\sim iid\ N(0, \Omega_2), \quad \Omega_2 = \begin{Bmatrix} \sigma_{\eta 0}^2 & \\ \rho\sigma_{\eta 0}\sigma_{\eta 1} & \sigma_{\eta 1}^2 \end{Bmatrix} && (12c) \\
\begin{Bmatrix} \nu_{s0} \\ \nu_{s1} \end{Bmatrix} &\sim iid\ N(0, \Omega_3), \quad \Omega_3 = \begin{Bmatrix} \sigma_{\nu 0}^2 & \\ \rho\sigma_{\nu 0}\sigma_{\nu 1} & \sigma_{\nu 1}^2 \end{Bmatrix} && (12d)
\end{aligned}$$

where A_{si} is the age of firms, E_{si} is the number of employees, N_{sit} is the net worth of firms, G_{sit} is the input growth, S_{sit} is the TFPR shocks, η_{si0} is the variability of the MRPK between firms within industries, η_{si1} is the variability of the relationship of net worth to the MRPK between firms within industries, ν_{s0} is the variability of the MRPK between industries, and ν_{s1} is the variability of the relationship of net worth to the MRPK between industries. I assume that both η_{si0} and ν_{si1} follow a normal distribution with a mean of zero and variance and covariance of Ω_2 and that both ν_{s0} and ν_{s1} follow a normal distribution with a mean of zero and variance and covariance of Ω_3. My parameters of interest are β_{01}, $\sigma_{\eta 1}^2$, and $\sigma_{\nu 1}^2$: β_{01} measures the correlation between net worth and MRPK, $\sigma_{\eta 1}^2$ estimates the variability of the correlation due to the variation between firms within industries, and $\sigma_{\nu 1}^2$ measures the variability of the correlation due to the variation between industries.

4 Results

4.1 Capital Misallocation and its Cyclicality

As mentioned before, I measure capital misallocation by the dispersion of MRPK within industries. To aggregate capital misallocation for each year, I calculate the weighted average of capital misallocation across industries by using sales to calculate an industry weight. Table 4 shows that average capital misallocation across countries tends to increase over time (see the last column in Table 4). To separate capital misallocation into trend components and cyclical components, I apply the Hodrick–Prescott (HP) filter.[15] I use the cyclical components to establish whether capital misallocation is procyclical or countercyclical. In the next section, to establish whether capital misallocation moves over business cycles, I plot the cyclical components of capital misallocation and the cyclical components of GDP.

Table 4: Capital misallocation

Year	Czech Republic	France	Germany	Italy	Poland	Portugal	Romania	Spain	Sweden	All
2005	1.43	1.26	1.49	1.43	1.28	1.11	1.35	1.28	1.45	1.34
2006	1.33	1.23	1.53	1.43	1.37	1.28	1.34	1.27	1.33	1.35
2007	1.39	1.26	1.55	1.44	1.32	1.29	1.29	1.31	1.35	1.36
2008	1.38	1.30	1.48	1.54	1.41	1.33	1.37	1.38	1.36	1.40
2009	1.40	1.32	1.47	1.59	1.45	1.34	1.40	1.44	1.37	1.42
2010	1.40	1.32	1.42	1.58	1.44	1.34	1.55	1.45	1.38	1.43
2011	1.38	1.28	1.43	1.58	1.48	1.35	1.55	1.47	1.40	1.43
2012	1.25	1.30	1.49	1.59	1.51	1.44	1.53	1.50	1.42	1.45
2013	1.28	1.29	1.49	1.61	1.51	1.43	1.61	1.51	1.42	1.46
2014	1.23	1.26	1.49	1.60	1.50	1.39	1.63	1.52	1.41	1.45

Note: The entries in the table denote the weighted capital misallocation. To aggregate the capital misallocation for each year for the given capital misallocation within industries, I calculate the weighted average of capital misallocation across industries by using sales to derive an industry weight.

[15] I use the Stata $tsfilter$ command by applying the HP filter to separate capital misallocation into trend components and cyclical components. I set the smoothing parameter for the HP filter to 6.25 for yearly data.

4.1.1 Cyclicality of Capital Misallocation: Business-Cycle Graph

To firmly establish that capital misallocation moves over business cycles, I plot the cyclical components of capital misallocation and GDP. Figure 4 shows the cyclicality of capital misallocation and GDP for Italy. Figure 8 illustrates all the other sample countries. For all these countries, in years in which the cyclical component of GDP is high, the cyclical component of capital misallocation is low. For example, for Italy in 2009, the cyclical component of capital misallocation is 0.033 and the cyclical component of GDP is -0.029. This result shows a negative correlation between capital misallocation and GDP. I find similar results for the other sample countries.

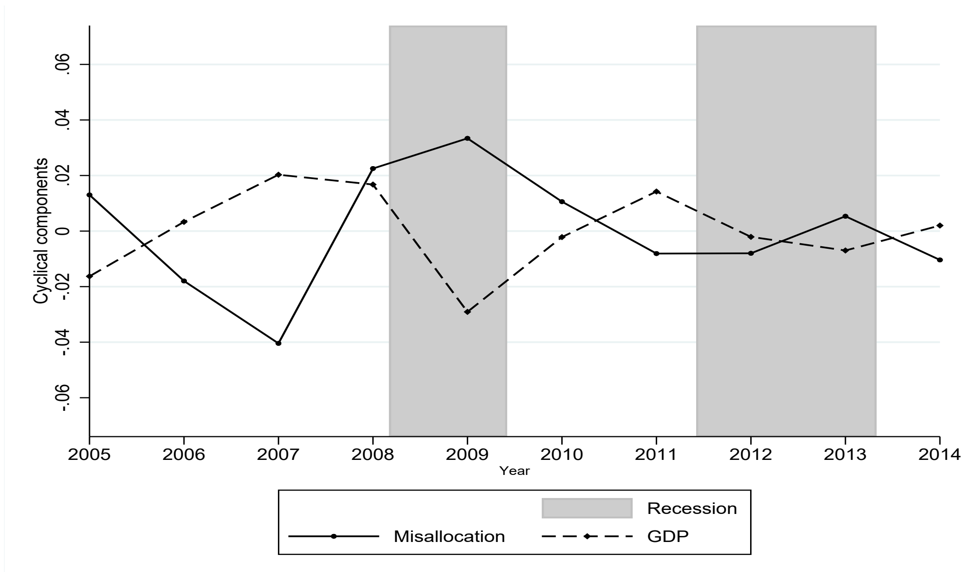
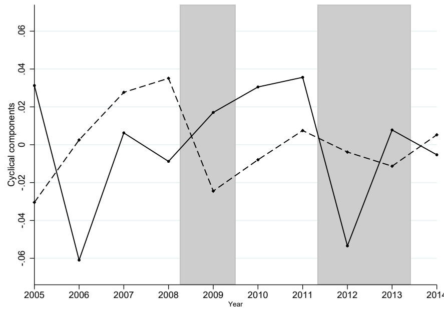
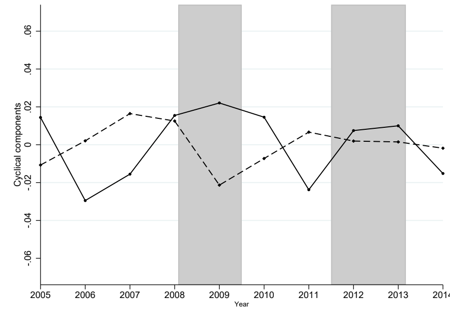


Figure 4: Cyclicality of capital misallocation and GDP (Italy)

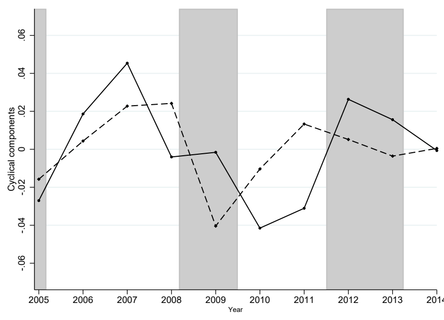
Note: Time series plot of the cyclical components of capital misallocation and real GDP, using the HP filter (smoothing parameter = 6.25). Shaded areas represent recessions.



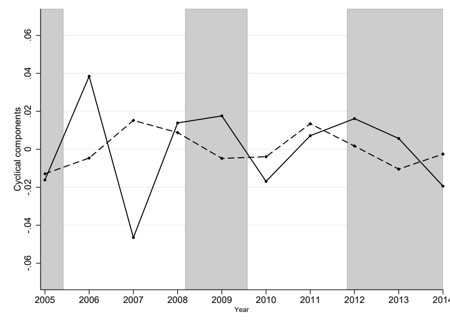
(a) Czech Republic



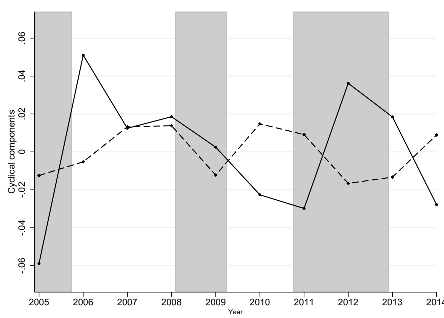
(b) France



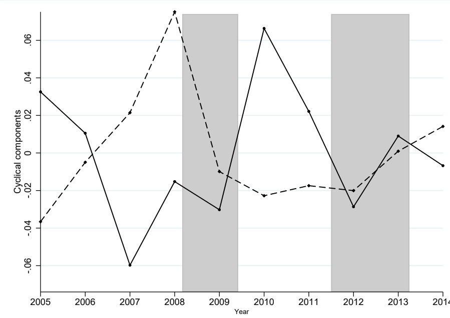
(c) Germany



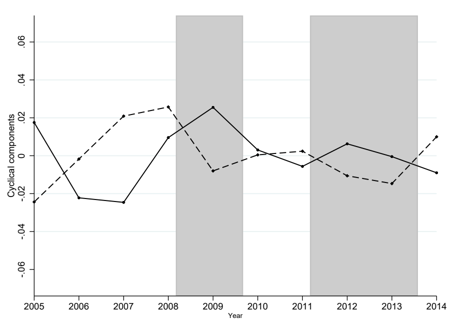
(d) Poland



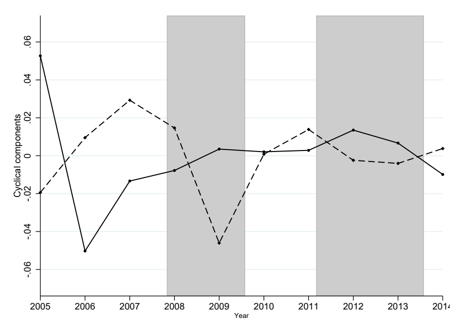
(e) Portugal



(f) Romania



(g) Spain



(h) Sweden

Figure 5: Cyclicality of capital misallocation and net worth of firms

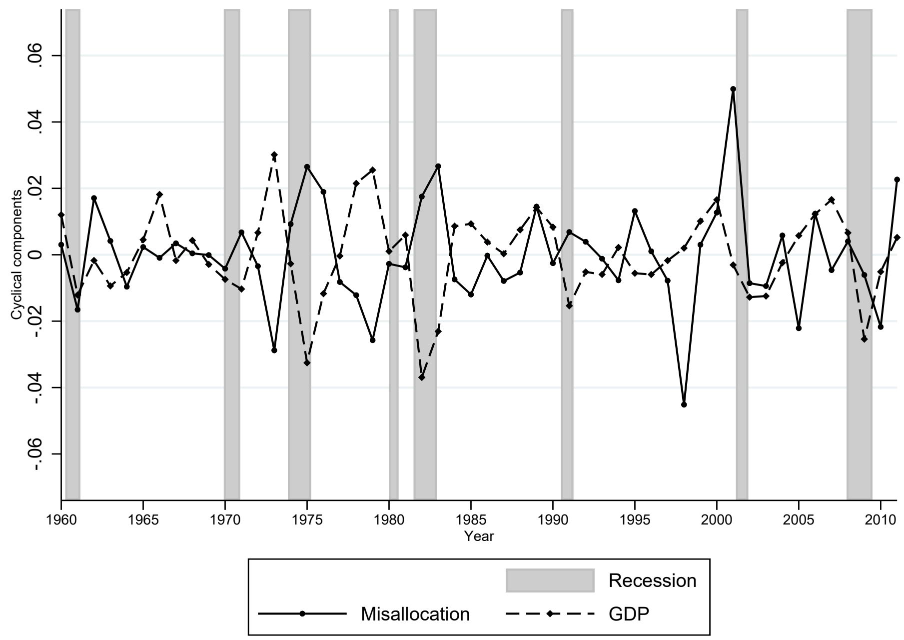
Note: Time series plot of the cyclical components of capital misallocation and real GDP, using the HP filter (smoothing parameter = 6.25). The solid line represents the cyclical components of capital misallocation and the dotted line represents the cyclical components of GDP. Shaded areas represent recessions.

4.1.2 Cyclicality of Capital Misallocation: Robustness Check

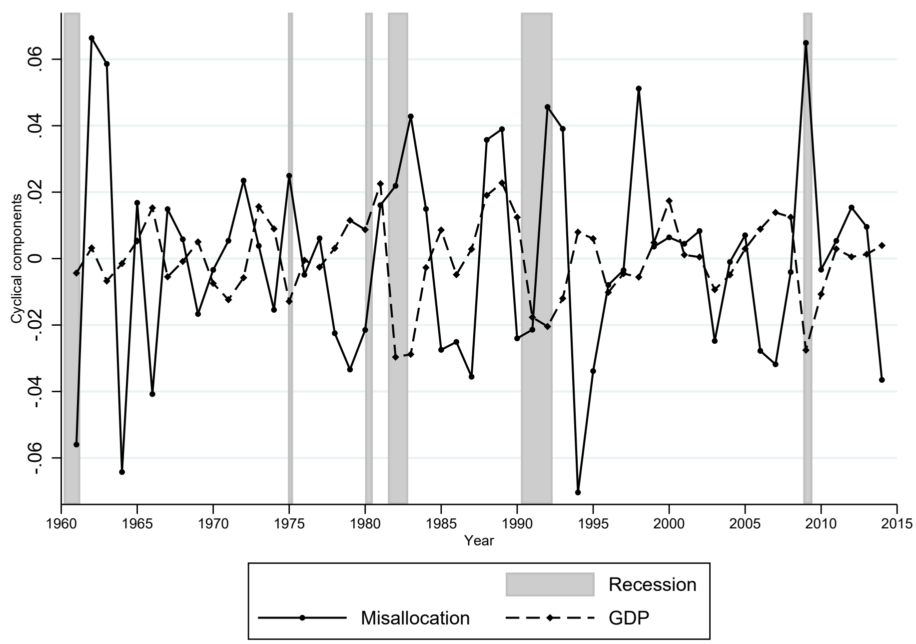
The number of years covered by the Amadeus and Orbis databases for European countries is admittedly limited. To test the robustness of my conclusion, therefore, I now apply the same method, using the Compustat database that has more than 50 years of data, for the United States and Canada. To use the Compustat database, I follow these steps. First, I measure the capital stock as expenditure on *property, plant, and equipment - total (net)*. Second, I drop firm-year observations if either sales or the capital stock are missing or zero (or negative). Third, since a lot of data on employees' salaries and wages are missing in this database, I cannot apply the same method as before to calculate the share of capital to compute MRPK. Hence, I use instead the NBER-CES database for the United States and Statistics Canada's KLEMS productivity database for Canada. Since the contribution of the share of capital is negligible in the MRPK calculation, this replacement does not reduce the validity of the conclusion. Fourth, for sales and the capital stock, I use deflators from the NBER-CES database for the United States and Statistics Canada's KLEMS productivity database for Canada (as explained in detail later). Finally, I remove observations below the first percentile or above the 99th percentile of the distribution for MRPK.

To calculate the share of capital for the United States, I subtract the ratio of total payroll and the total value of shipments and the ratio of the total cost of materials and total value of shipments from one. If this share of capital is negative, I use that share at the industry group or industry sector level. To calculate the share of capital for Canada, I use the ratio of the cost of capital services and total cost of inputs. The total cost of inputs includes the cost of labor input, cost of capital services, and cost of materials input.

Since the NBER-CES database is available up to 2011, I use the Compustat database for 1960 to 2011 for the United States. Since Statistics Canada's KLEMS database is available for 1961 to 2014, I use the database for that period for Canada. To aggregate the dispersion of MRPK for each year, I use an unweighted mean. I use recession data from the NBER database for the United States and the C.D. Howe Institute report for Canada. Figure 6 shows the cyclicality of capital misallocation for the United States and Canada. These graphs depict a negative correlation between capital misallocation and GDP.



(a) United States



(b) Canada

Source: Compustat

Note: Time series plot of the cyclical components of capital misallocation and real GDP, using the HP filter (smoothing parameter = 6.25). Shaded areas represent recessions.

Figure 6: Cyclicality of capital misallocation and GDP (United States and Canada)

4.1.3 Cyclicality of Capital Misallocation: Correlation Analysis

To precisely establish the degree of the negative association between the cyclical components of capital misallocation and GDP, I calculate the correlation between them. To take one example from Table 5, the correlation between the cyclical components of capital misallocation and GDP for Italy is -0.64. Although the correlations for some countries are not as strong as the correlation for Italy, they still support the aforementioned result. Thus, both the results from European countries and the results from the United States and Canada further establish that capital misallocation is low during booms and high during recessions, or countercyclical.

Much of the aggregate cyclicality of capital misallocation could be driven by a subset of specific industries. To understand the cyclicality of capital misallocation at an industry level, I identify industries that are more responsive to business cycles. For this industry-specific analysis, I compare durable with non-durable industries and high external finance-dependent with low external finance-dependent industries.

It seems reasonable to suspect that the responsiveness between durable and non-durable industries may differ since the purchase of durable goods can be postponed during recessionary periods. Thus, consumer expenditure on durable goods tends to fluctuate with business cycles. Conversely, regardless of the economic conditions, consumers will always buy non-durable goods. A natural implication is that durable industries would be more responsive to business cycles than non-durable industries. To test this hypothesis, I first divide my sample into durable and non-durable industries. I separate out the cyclical components of capital misallocation and GDP and then calculate the correlation between them. The correlations in Table 5 show that capital misallocation for both durable and non-durable industries moves over business cycles; however, durable industries show a more cyclical pattern than non-durable industries. For example, the correlation for durable industries in Italy is -0.68, whereas the correlation for non-durable industries is -0.49.

Next, by using the measure of external finance dependence developed by Rajan and Zingales (1998), I compare high external finance-dependent with low external finance-dependent industries. Following Gopinath et al. (2017), I classify industries as "high dependence" if their measure of dependence is higher than the median dependence and "low dependence" if their measure of dependence is lower than the median dependence. Table 5 also presents the correlations between the cyclical components of capital misallocation and GDP for high and low external finance-dependent industries. These correlation figures show that capital misallocation for both high and low external finance-dependent industries moves over business cycles. However, industries relying heavily on external finance show more cyclicality in some countries. For example, in Italy, the correlation between the cyclical components of capital misallocation and GDP for high external finance-dependent industries is -0.65, whereas the correlation for low external finance-dependent industries is -0.59.

Table 5: Correlations between the cyclical components of capital misallocation and GDP

Country	**Overall**	**Durable**	**Non-durable**	**Highly dependent**	**Less dependent**
Czech Republic	-0.25	-0.14	-0.38	-0.22	-0.32
France	-0.51	-0.43	-0.57	-0.40	-0.63
Germany	0.34	-0.52	0.52	-0.38	0.57
Italy	-0.64	-0.68	-0.49	-0.65	-0.59
Poland	-0.22	-0.24	-0.18	-0.02	-0.28
Portugal	-0.21	-0.22	-0.19	-0.28	-0.18
Romania	-0.47	-0.57	0.11	-0.66	-0.14
Spain	-0.45	-0.17	-0.29	-0.14	-0.37
Sweden	-0.47	-0.58	0.33	0.24	-0.54
All	-0.32	-0.39	-0.13	-0.28	-0.28
USA	-0.36				
Canada	-0.33				

Note: Each cell represents the correlation. The unit of analysis is year.

4.1.4 Cyclicality of Capital Misallocation: Regression Analysis

To establish that capital misallocation changes with the business cycle, I regress capital misallocation at the industry level on the intensity of business cycles. Since I use yearly data instead of quarterly data,[16] I measure the intensity of business cycles by the percentage

[16] I could use a dummy variable for recessionary periods if I had quarterly data. It is hard to find firm-level quarterly data across countries.

of months in a recession for a given year (*Recessions*). I include a vector of the covariates to account for firm, industry, and country heterogeneity. I add the mean age of firms and total employment, which are in log scale. In addition, I include the normalized Herfindahl index[17] (an indicator of the level of competition among firms) of the industry to capture the scale effects. Furthermore, I include openness measured by trade share, which is calculated by adding exports to imports and dividing the sum by outputs. Moreover, I add a vector for institutional quality to this estimation. These indicators are voice and accountability, political stability and absence of violence, government effectiveness, the regulatory quality, rule of law, and control of corruption. I also include industry dummies to capture the effects of the unobservable and time-invariant industry characteristics, year dummies to capture the time trends, and country dummies to capture the country-specific fixed effects. Since the number of observations varies across industries, I include those numbers as a weight in the estimation. Table 6 shows the effect of the intensity of business cycles on capital misallocation. The results show that an increase in the intensity of business cycles leads to increased capital misallocation.

To identify industries highly susceptible to business cycles, I compare durable with non-durable industries by including an interaction term between recessions and durable industries (second specification) and compare high external finance-dependent with low external finance-dependent industries by including an interaction term between recessions and dependence industries (third specification). Table 6 also shows that the effect of the intensity of business cycles on capital misallocation is stronger for durable industries than for non-durable industries and stronger for high external finance-dependent industries than for low external finance-dependent industries.

[17] To control for market concentration, I use the normalized Herfindahl index, $H^* = \frac{H-\frac{1}{N}}{1-\frac{1}{N}}$, where $H = \sum_{i=1}^{N} S_i^2$, N is the number of firms within industries, and S_i is the market share measured by the sales of firms i within industries.

Table 6: Effect of the intensity of business cycles on capital misallocation

Dependent variable: Capital Misallocation			
	First Specification	Second Specification	Third Specification
Recessions	0.047***	0.040***	0.040***
	(0.007)	(0.008)	(0.008)
Recessions*Durable		0.011**	
		(0.005)	
Recessions*Dependence			0.010**
			(0.005)
Mean age of firms	-0.040	-0.040	-0.040
	(0.026)	(0.026)	(0.026)
Total employment	-0.048***	-0.048***	-0.048***
	(0.006)	(0.006)	(0.006)
Normalized Herfindahl index	0.326**	0.326**	0.326**
	(0.160)	(0.160)	(0.160)
Openness	0.007	0.008	0.007
	(0.014)	(0.014)	(0.014)
Institutional quality	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Country	Yes	Yes	Yes
N	17071	17071	17071
R^2	0.63	0.63	0.63

Note: An observation is a country, a year, and an industry. *Recessions* is the percentage of months in a recession for a given year. *Durable* is an indicator for durable industries and *Dependence* is an indicator for external finance-dependent industries. The mean age of firms and total employment are in log scale. I use the normalized Herfindahl index as $H^* = \frac{H-\frac{1}{N}}{1-\frac{1}{N}}$, where $H = \sum_{i=1}^{N} S_i^2$, N is the number of firms, and S_i is the market share (measured by sales) of firm i. Openness is measured by trade share, which is calculated by adding exports to imports and dividing the sum by outputs. I use the vector of *Institutional quality* given by the World Bank Governance Indicators. These indicators are voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption. I use the number of firms for an industry as a weight. I estimate the cluster standard errors, which are in parentheses, at the country and industry levels. ***, **, and * indicate statistically significant coefficients at the one, five, and 10 percent levels, respectively.

4.2 Factors Associated with Capital Misallocation

As mentioned before, I use the unconditional linear mixed model to decompose capital misallocation, as measured by the variance components of $MRPK_{sit}$, into misallocation due to the variation between firms within industries (σ_η^2), variation between industries (σ_ν^2), and variation within firms over time (σ_ϵ^2). To estimate this unconditional linear mixed model, I use the *lme*4 package in R.[18]

Table 7 shows the estimates for the unconditional linear mixed model. The results show that in all the sample countries, most of the $MRPK_{sit}$ variance, or capital misallocation, is due to the variation between firms within industries. For example, in Italy, $MRPK_{sit}$ variance due to the variation between firms within industries is 2.01, whereas the variation between industries is only 0.59 and the variation within firms over time is only 0.47. With the exception of Czech Republic and Spain, the other sample countries show a similar result.

Table 7 also presents the *percentage* of $MRPK_{sit}$ variance components due to the variation between firms within industries (ρ_η), variation between industries (ρ_ν), and variation within firms over time (ρ_ϵ). The result shows that, in Italy, the variation between firms within industries contributes 65.53 percent of total $MRPK_{sit}$ variance, the variation between industries contributes 19.20 percent of the variance, and the variation within firms over time contributes 15.27 percent of the variance. With the exception of Czech Republic and Spain, the other countries in the sample show similar results. In general, this result shows that more than 50 percent of $MRPK_{sit}$ variance is caused by the variation between firms within industries. Thus, more than 50 percent of capital misallocation is due to the variation between firms within industries.

[18]Since the number of observations and number of industries are large for some sample countries, it is convenient to estimate the unconditional linear mixed model in R instead of *PROC MIXED* in SAS and using the *mixed* command in Stata.

Table 7: Decomposition of capital misallocation

Variables	Czech Republic	France	Germany	Italy	Poland	Portugal	Romania	Spain	Sweden	All
Dependent variable: $MRPK_{sit}$										
Fixed effect										
Intercept, β_{00}	-1.88	0.61	-0.46	0.04	-0.69	-1.22	-0.79	-0.95	-0.41	-0.64
	(0.14)	(0.05)	(0.08)	(0.05)	(0.08)	(0.08)	(0.07)	(0.09)	(0.07)	(0.08)
Random effects										
Between firms within industries, σ_η^2	1.82	1.13	1.97	2.01	2.23	1.63	1.70	1.90	1.89	1.81
Between industries, σ_ν^2	3.81	0.51	1.10	0.59	1.12	0.92	0.84	1.67	0.59	1.24
Over time within firms, σ_ϵ^2	0.54	0.46	0.29	0.47	0.47	0.45	0.66	0.50	0.57	0.49
Variance components (percentage)										
Between firms within industries, ρ_η	29.51	53.75	58.67	65.53	58.33	54.41	53.10	46.78	62.06	53.57
Between industries, ρ_ν	61.69	24.15	32.64	19.20	29.35	30.64	26.14	40.92	19.38	31.57
Over time within firms, ρ_ϵ	8.80	22.10	8.69	15.27	12.32	14.95	20.76	12.30	18.56	14.86
R^2	0.91	0.81	0.93	0.86	0.89	0.87	0.83	0.88	0.83	0.87
Number of firms	18796	110779	24709	170830	16691	39643	42278	92703	19684	59,568
Number of industries (four-digit NACE)	193	213	167	276	169	156	187	220	146	192
Number of observations	108316	648079	95263	947060	89915	221905	211288	570918	124201	3,016,945

Note: Standard errors in parentheses. To decompose capital misallocation (as measured by the variance components of $MRPK_{sit}$), I use an unconditional linear mixed model. To estimate this model, I use the *lme4* package in R. The result shows that most of the $MRPK_{sit}$ variance, capital misallocation, is due to the variation between firms within industries (ρ_η).

Since the variation between firms within industries explains most of the total $MRPK_{sit}$ variance, I focus, in this section, on the firm-level factors that may be associated with capital misallocation. To identify the relative importance of these firm-level factors, I estimate the R square value[19] by using both simple and multiple regressions. To remove the year and industry effects on the R square value, I apply the Frisch–Waugh theorem of regression partitioning.

For the simple regression, I use the following steps of the Frisch–Waugh theorem:

1. I first regress MRPK on both the year and the industry dummies to obtain the residual of MRPK.

2. I then regress a predictor on the same year and industry dummies to obtain the residual of the predictor.

3. Finally, I regress the residual of MRPK on the residual of the predictor without a constant to estimate the R square value, which explains how much of the variation between firms within industries is explained by that predictor.

For the multiple regression, I regress the residual of MRPK on the residual of all the predictors without a constant to estimate the R square value. To decompose the R square value of this multiple regression, I apply the Feldman method (*pmvd*), using the R package *relaimpo* of Groemping (2006).

Tables 8 and 9 present the firm-level factors associated with capital misallocation for both the simple and the multiple regressions. The results of both regressions show that, in general, the net worth of firms alone can explain more MRPK variation than all the other examined factors combined. For Italy, the R square value for the simple regression of net worth is 4.86. This means that around five percent of the MRPK variation between firms within industries is explained by net worth.

To further refine the contribution of net worth to capital misallocation, I examine the contribution of net worth according to firm size. To identify whether capital misallocation differs by firm size, I divide the sample into three groups based on the Amadeus classification

[19]The R square value indicates the proportion of the variance in the dependent variable predictable from the independent variable(s).

for firm size: small, medium, and large. I consider both large and very large firms as a single group because of the small number of observations in these two groups.

Table 8: MRPK variation between firms within industries by size (simple regression)

Regressors	Czech Republic	France	Germany	Italy	Poland	Portugal	Romania	Spain	Sweden	All
Overall										
Age	2.47	0.46	0.12	2.86	1.69	0.07	2.70	0.16	0.10	1.18
Labor	2.55	1.02	2.45	0.64	5.78	1.38	0.08	0.00	0.16	1.56
Net worth	6.87	0.65	1.33	4.86	10.82	2.91	5.16	1.42	1.95	4.00
Leverage	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00
Input growth	0.32	0.92	0.00	0.22	0.19	0.07	1.00	0.46	0.09	0.36
TFPR shock	0.75	2.24	0.29	1.55	0.97	1.36	1.93	0.90	0.87	1.21
Small										
Age	1.99	2.41	0.14	1.47	1.31	0.03	2.35	0.25	0.00	1.11
Labor	0.00	0.06	0.39	0.04	1.72	0.35	0.01	0.09	0.05	0.30
Net worth	2.76	0.04	0.41	5.08	7.33	2.00	4.86	2.11	1.69	2.92
Leverage	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.08	0.01
Input growth	0.73	1.59	0.00	0.10	0.60	0.05	1.12	0.50	0.13	0.54
TFPR shock	1.09	2.62	0.38	1.45	1.65	1.42	2.23	0.97	0.88	1.41
Medium-sized										
Age	4.11	0.14	0.03	4.79	2.11	0.53	3.30	0.18	0.90	1.79
Labor	2.78	1.80	1.64	1.56	6.03	1.41	0.14	0.48	1.10	1.88
Net worth	10.12	2.76	0.73	9.95	15.47	3.44	9.20	4.28	4.70	6.74
Leverage	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Input growth	0.35	0.30	0.00	0.45	0.34	0.50	0.97	0.38	0.05	0.37
TFPR shock	0.77	1.96	0.46	1.75	1.08	1.50	1.61	0.86	0.99	1.22
Large										
Age	0.08	0.37	0.11	2.33	0.33	0.73	1.44	0.03	0.80	0.69
Labor	1.27	5.77	4.27	4.92	2.48	2.78	2.92	2.09	4.41	3.43
Net worth	6.45	5.30	1.29	7.85	8.53	1.77	5.64	3.02	5.95	5.09
Leverage	0.02	0.00	0.00	0.04	0.00	0.00	0.03	0.01	0.05	0.02
Input growth	0.00	0.00	0.00	0.20	0.02	0.00	0.68	0.06	0.01	0.11
TFPR shock	0.39	0.90	0.19	1.51	0.27	1.20	0.76	0.41	0.64	0.70

Note: Each cell represents the R square value estimated by using the Frisch–Waugh theorem. For the simple regression, I estimate the individual regression and then calculate the R square value.

Table 9: MRPK variation between firms within industries by size (multiple regression)

Regressors	Czech Republic	France	Germany	Italy	Poland	Portugal	Romania	Spain	Sweden	All
Overall										
Age	0.94	0.74	0.01	1.08	0.04	0.47	1.07	0.05	0.05	0.49
Labor	0.48	0.14	1.69	0.59	0.03	0.00	1.90	0.84	0.59	0.70
Net worth	7.23	1.53	1.07	4.41	11.60	3.01	5.62	1.84	2.15	4.27
Leverage	0.14	0.00	0.01	0.00	0.10	0.01	0.01	0.01	0.16	0.05
Input growth	0.25	0.63	0.01	0.17	0.11	0.12	1.58	0.44	0.14	0.38
TFPR shock	0.82	2.04	0.25	1.62	1.21	1.41	2.44	0.94	0.91	1.29
R square	9.86	5.07	3.03	7.88	13.09	5.01	12.62	4.12	4.01	7.19
Small										
Age	1.38	1.87	0.26	0.13	0.13	0.72	1.02	0.02	0.21	0.64
Labor	0.39	0.02	0.57	0.10	0.04	0.00	0.98	0.79	0.57	0.38
Net worth	2.95	0.34	0.80	5.53	7.09	2.20	4.84	2.37	1.94	3.12
Leverage	0.10	0.00	0.03	0.01	0.49	0.01	0.01	0.01	0.21	0.10
Input growth	0.57	1.10	0.01	0.15	0.21	0.11	1.90	0.47	0.23	0.53
TFPR shock	1.19	2.48	0.53	1.57	2.17	1.48	2.86	1.03	0.94	1.58
R square	6.57	5.80	2.20	7.48	10.13	4.51	11.61	4.68	4.10	6.34
Medium-sized										
Age	1.55	0.09	0.01	1.44	0.00	0.14	1.04	0.33	0.01	0.51
Labor	0.01	0.60	0.91	0.00	1.29	0.14	1.39	0.02	0.01	0.49
Net worth	10.00	2.55	2.08	9.52	13.54	3.29	9.06	4.21	4.76	6.56
Leverage	0.20	0.00	0.03	0.00	0.16	0.05	0.33	0.03	0.16	0.11
Input growth	0.08	0.40	0.00	0.09	0.14	0.24	0.96	0.26	0.01	0.24
TFPR shock	0.67	1.75	0.43	1.49	1.17	1.38	1.72	0.76	0.88	1.14
R square	12.51	5.40	3.46	12.55	16.30	5.24	14.50	5.62	5.85	9.05
Large										
Age	0.39	0.01	0.00	0.72	0.02	0.09	0.33	0.45	0.02	0.23
Labor	0.18	4.23	3.83	1.34	0.00	2.53	7.96	0.77	1.14	2.44
Net worth	6.68	2.41	0.61	6.86	7.37	0.34	9.86	2.48	5.29	4.66
Leverage	0.19	0.01	0.01	0.01	0.14	0.01	0.18	0.01	0.18	0.08
Input growth	0.00	0.02	0.00	0.01	0.01	0.04	0.43	0.03	0.13	0.08
TFPR shock	0.39	0.60	0.14	1.24	0.30	0.98	0.83	0.38	0.48	0.59
R square	7.83	7.29	4.60	10.16	7.84	3.99	19.60	4.10	7.25	8.07

Note: Each cell represents the R square value estimated by using the Frisch–Waugh theorem. For this regression, I estimate the multiple regression, calculate the R square value, and then decompose the R square value by using the Feldman method (pmvd).

Tables 8 and 9 also show the MRPK variation between firms within industries by firm size. The results highlight that the net worth of firms explains more MRPK variation in the case of medium-sized firms than it does for small and large firms. One possible explanation is that small firms have less access to finance for covering the cost of capital compared with large firms that have easy access; meanwhile, medium-sized firms rely heavily on external finance but have limited access to it.

To show the overall importance of the net worth of firms for explaining capital misallocation, I calculate the average R square value for both the simple and the multiple regressions across countries. I find that the net worth of medium-sized firms explains around seven percent of the MRPK variation between firms within industries.

I then estimate, by year, how much net worth contributes to MRPK variation. I consider only medium-sized firms since this group explains more MRPK variation. Table 10 presents MRPK variation due to net worth among medium-sized firms by year. For all the sample countries, net worth explains more MRPK variation in 2008 and onwards. One possible explanation is that the global financial crisis in that period led to a tighter credit market and more misallocation.

Table 10: MRPK variation and the net worth of medium-sized firms by year (percentage)

Year	Czech Republic	France	Germany	Italy	Poland	Portugal	Romania	Spain	Sweden	All
2005	3.34	1.36	0.35	3.26	5.05	0.41	4.42	1.45	2.40	2.45
2006	3.39	1.56	0.60	2.87	3.99	0.92	4.37	1.41	2.45	2.40
2007	3.17	1.86	0.32	2.24	5.18	0.95	1.87	1.63	3.34	2.29
2008	4.32	2.29	0.66	7.05	5.80	0.97	3.67	1.31	3.81	3.32
2009	4.90	2.41	0.42	8.56	7.70	1.28	4.90	1.51	3.57	3.92
2010	4.44	2.37	1.47	8.92	8.52	1.60	6.02	1.89	3.52	4.31
2011	5.57	2.77	1.81	8.29	8.99	1.77	6.47	2.17	4.16	4.67
2012	6.15	2.90	1.86	7.94	10.48	1.93	6.41	2.71	4.26	4.96
2013	7.12	3.19	2.05	8.44	10.90	2.34	7.20	3.37	4.39	5.44
2014	7.91	3.54	6.30	8.40	12.86	2.46	7.64	3.78	4.21	6.34

Note: Each cell represents the R square value estimated by using the Frisch–Waugh theorem. I estimate the individual regression and then calculate the R square value.

4.3 Factors Associated with the Cyclicality of Capital Misallocation

To show the firm-level factors associated with the cyclicality of capital misallocation, I follow a three-step process that considers only the net worth of medium-sized firms since net worth alone explains more MRPK variation than all the other examined factors combined. First, I separate out the cyclical components of capital misallocation while controlling for the net worth of firms. The dotted line in Figure 7 shows these cyclical components. Second, I separate out the cyclical components of capital misallocation without controlling for the net worth of firms. The solid line in Figure 7 shows these cyclical components. For both cases, I remove the industry fixed effect. Third, I compare both these cyclical components of capital misallocation. Figure 7, for Italy, shows a deviation between the two lines. I find similar results for all the other sample countries (Figure 8). Thus, I conclude that the net worth of firms explains not only capital misallocation but also its cyclicality.

To make my conclusion more precise, I calculate the ratio of the total absolute deviation between these two lines (solid line and dotted line in Figure 7) and the total of all cyclical components (solid line in Figure 7). Table 11 shows that the percentage of the cyclicality of capital misallocation is explained by the net worth of firms for all the sample countries. Overall, I find that the net worth of medium-sized firms explains 29.08 percent of the cyclicality of capital misallocation.

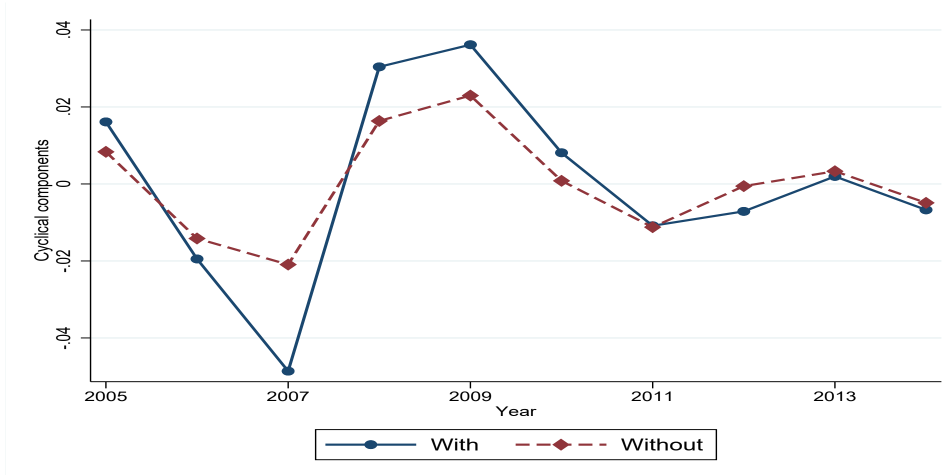
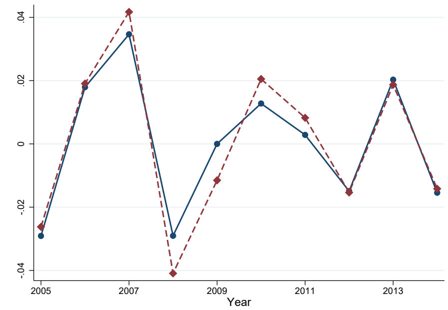
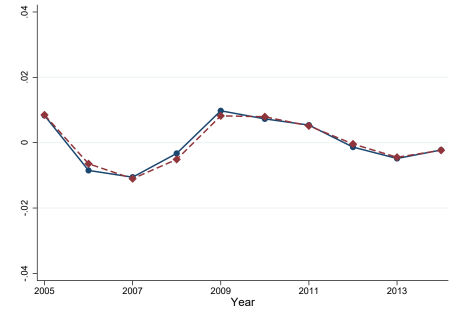


Figure 7: Cyclicality of capital misallocation and the net worth of firms (Italy)

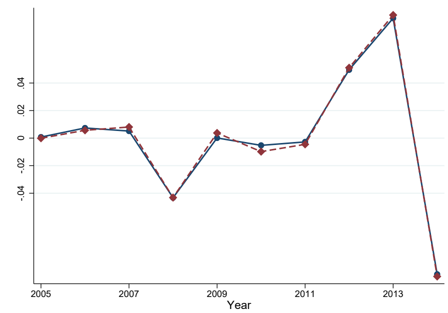
Note: Time series plot of the cyclical components of capital misallocation with and without the effect of net worth.



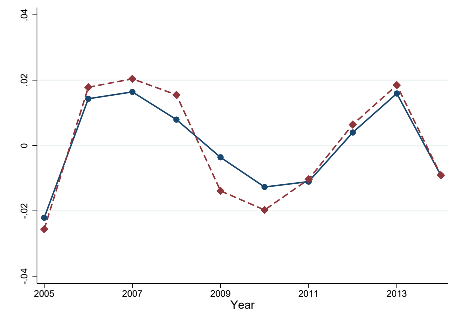
(a) Czech Republic



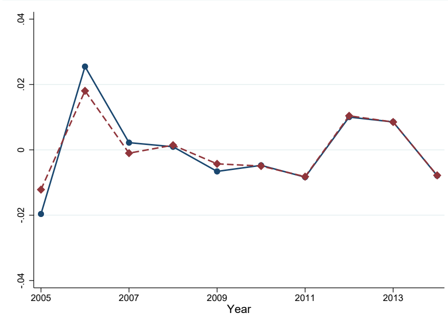
(b) France



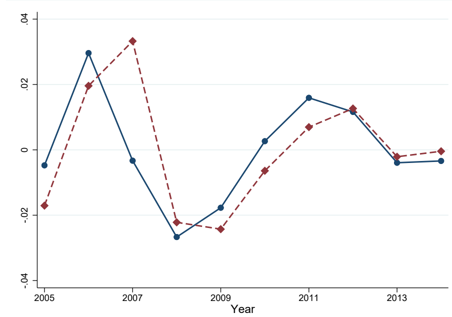
(c) Germany



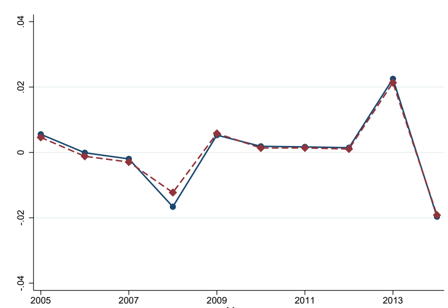
(d) Poland



(e) Portugal



(f) Romania



(g) Spain

(h) Sweden

Figure 8: Cyclicality of capital misallocation and the net worth of firms

Note: Time series plot of the cyclical components of capital misallocation with and without the effect of net worth.

Table 11: Cyclicality of capital misallocation and the net worth of firms

Country	**Cyclicality of capital misallocation**
Czech Republic	28.74
France	13.64
Germany	6.98
Italy	46.03
Poland	35.54
Portugal	23.02
Romania	78.50
Spain	13.94
Sweden	15.36
All	29.08

Note: Each cell represents the percentage of the cyclicality of capital misallocation explained by the net worth of firms.

4.4 MRPK and Net Worth of Firms

To estimate the effect of net worth on MRPK, I use the conditional linear mixed model. I use several covariates in the estimation, as is standard in the misallocation literature. To examine the effects of these covariates, I first need to determine the appropriate level at which each covariate should enter the mixed model. As mentioned before, I include the input growth and TFPR shocks in the "within firms over time" category and age and size (as measured by the number of employees) in the "between firms within industries" category.

Table 12 shows the effect of net worth on MRPK. In general, more than 90 percent of MRPK variation is explained by this specification. The result shows that the effect of net worth on MRPK is negative and statistically significant. For example, the average coefficient for all the sample countries is -0.27. That is, if net worth within firms increases by one percentage point over time, then one would expect MRPK to decrease by 27 percentage points.

Table 12 also shows that the effect of net worth on MRPK varies more between firms within industries than between industries. For the net worth slope coefficient, I find $-0.27 \pm 1.96 \times \sqrt{0.60}$, giving an interval for between firms within industries from -1.79 to 1.25. This means that 95 percent of firms have net worth slopes between -1.79 and 1.25. By contrast, 95 percent of industries have net worth slopes between -0.89 and 0.35. Thus, the effect of net worth on MRPK varies more between firms within industries than between industries, confirming the aforementioned decomposition result.

Table 12: Correlation between MRPK and net worth

Variables	Czech Republic	France	Germany	Italy	Poland	Portugal	Romania	Spain	Sweden	All
Dependent variable: $MRPK_{sit}$										
Fixed effect										
Intercept, β_{00}	-1.60	0.28	0.02	-0.07	-0.66	-1.72	-0.89	-1.10	-1.20	-0.77
	(0.14)	(0.05)	(0.09)	(0.05)	(0.09)	(0.08)	(0.07)	(0.09)	(0.07)	(0.08)
Age, β_{10}	-0.22	0.21	0.01	-0.03	-0.03	0.21	-0.14	-0.12	0.28	0.02
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Labor, β_{20}	0.08	-0.04	-0.14	0.11	-0.01	0.03	0.21	0.24	0.08	0.06
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Net worth, β_{01}	-0.38	-0.19	-0.07	-0.34	-0.42	-0.22	-0.31	-0.26	-0.20	-0.27
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Input growth, π_2	0.29	-0.22	0.25	0.25	0.25	0.26	0.37	0.42	0.27	0.24
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
TFPR shocks, π_3	0.69	1.26	0.62	0.83	0.82	0.76	0.55	0.81	0.74	0.79
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Random effects										
Between firms within industries, $\sigma^2_{\eta 0}$	1.63	0.96	1.84	1.83	1.47	1.61	1.56	1.81	1.90	1.62
Net worth, $\sigma^2_{\eta 1}$	0.84	0.29	0.10	0.81	0.57	0.63	0.58	0.85	0.71	0.60
Covariance, $\rho\sigma_{\eta 0}\sigma_{\eta 1}$	0.00	0.01	0.01	0.08	-0.22	0.17	0.15	0.09	0.18	0.05
Between industries, $\sigma^2_{\nu 0}$	3.68	0.46	1.03	0.55	1.04	0.90	0.86	1.62	0.59	1.19
Net worth, $\sigma^2_{\nu 1}$	0.02	0.01	0.00	0.01	0.01	0.01	0.02	0.00	0.02	0.01
Covariance, $\rho\sigma_{\nu 0}\sigma_{\nu 1}$	0.04	0.00	0.01	0.02	0.00	0.02	0.03	0.01	0.00	0.01
Over time within firms, σ^2_{ϵ}	0.38	0.33	0.21	0.28	0.21	0.34	0.47	0.35	0.44	0.33
R^2	0.94	0.88	0.95	0.92	0.95	0.91	0.88	0.92	0.87	0.91
Number of firms	18203	81350	18626	147039	12704	38965	42007	90448	19482	52,092
Number of industries	193	213	167	276	169	156	187	220	146	192
Number of observations	102697	309030	66989	710090	40963	210944	210495	542246	123172	2,316,626

Note: Standard errors in parentheses. The result shows a negative correlation between MRPK and net worth (β_{10}). This correlation varies more between firms within industries ($\sigma^2_{\eta 1}$) than between industries ($\sigma^2_{\nu 1}$).

5 Conclusion

Since capital misallocation can lower TFP, this explains a large part of cross-country TFP differences. However, the possible cyclicality of capital misallocation has not been intensively studied. In this study, in addition to establishing the cyclicality of capital misallocation, I identify the sources and factors that account for capital misallocation and its cyclicality.

I use European firm-level data for 2005 to 2014 and calculate capital misallocation by the dispersion of MRPK. To provide empirical evidence for the cyclicality of capital misallocation, I use a business-cycle graph, correlation, and simple ordinary least squares regression. I establish that capital misallocation is countercyclical (i.e., higher during recessions and lower during booms). I also confirm this result by using Compustat data for the United States and Canada. By estimating the effect of the intensity of business cycles on capital misallocation, I provide further evidence for the countercyclicality of capital misallocation.

As for the sources of capital misallocation, using the decomposition method, I estimate that more than 50 percent is due to the variation between firms within industries. Hence, I focus on the firm-level factors associated with capital misallocation by estimating the relative importance of each. I find that the net worth of firms alone explains more capital misallocation than all the other examined firm-level factors combined. Overall, among medium-sized firms, net worth explains approximately seven percent of capital misallocation between firms within industries.

As for the factors associated with the cyclicality of capital misallocation, I consider only the net worth of firms because it explains more variation than the other factors. I find that the net worth of firms explains not only capital misallocation but also its cyclicality. To be more precise, the net worth of medium-sized firms explains around one-quarter of the cyclicality of the capital misallocation within industries. This finding suggests that financial frictions may play a role.

Since the net worth of firms can explain more capital misallocation, I use a conditional linear mixed model to estimate the effect of net worth on MRPK. For all the sample countries, I find that the effect of net worth on MRPK is negative and statistically significant. I also find that the effect of net worth on MRPK varies more between firms within industries than between industries, confirming the aforementioned decomposition result.

This study is an important first step toward documenting the cyclicality of capital misallocation and factors associated with it. Future researchers might attempt to understand whether the cyclicality of capital misallocation causes the cyclicality of TFP by developing a theoretical model.

Appendix

A Capital Misallocation and Credit Constraints

This section describes the linkage between aggregate TFP and the resource misallocation that results from firm-level distortions by using the theoretical model proposed by Hsieh and Klenow (2009). Instead of applying exogenous taxes on output and capital, I consider the distortions due to the credit constraints arising from the asymmetric information between lenders and borrowers.

I assume that a representative producer of a final good Y at time t (this index is omitted) faces a perfectly competitive output and input market. This final good producer combines the output Y_s of manufacturing industries by using a Cobb–Douglas technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}, \quad where \sum_{s=1}^{S} \theta_s = 1 \tag{13}$$

where θ_s denotes the industry shares. I set the final output as the numeraire such that its price $P = 1$. The industry output Y_s of industry s is itself a CES aggregate of the M_s differentiated products Y_{si} produced by individual firms:

$$Y_s = \left[\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{14}$$

where σ denotes the elasticity of substitution between firms. The production function for each differentiated product Y_{si} is given by a Cobb–Douglas function:

$$Y_{si} = A_{si} K_{si}^{\alpha_K} L_{si}^{\alpha_L} M_{si}^{\alpha_M}, \quad \alpha_K + \alpha_L + \alpha_M = 1 \tag{15}$$

where K_{si} is the capital input, L_{si} is the labor input, and M_{si} is materials. Furthermore, I assume that the production function and α's are industry-specific for a given country. A_{si} is an idiosyncratic productivity component. The profit maximization of firm i in industry s is given by

$$\max_{Y_{si}, K_{si}, L_{si}, M_{si}} P_{si} Y_{si} - R K_{si} - w L_{si} - m M_{si} \tag{16}$$

subject to $Y_{si} = A_{si} K_{si}^{\alpha_K} L_{si}^{\alpha_L} M_{si}^{\alpha_M}$ and the credit constraint:

$$\tau R K_{si} + w L_{si} + m M_{si} \leq W(z_{si}, \gamma), \quad \tau \geq 1 \tag{17}$$

where z_{si} is a firm characteristic (e.g., the net worth of firms), γ parametrizes the financial system (i.e., a better financial system allows you to borrow more against each dollar of collateral), and τ parametrizes the intensity of asymmetric information. $\tau = 1$ corresponds to perfect information. W is increasing in z_{si} (firms with higher net worth are less constrained) and γ (better financial systems are associated with higher values of γ). I use this form of credit constraint because it allows me to derive a result similar to that of Hsieh and Klenow (2009). The first-order conditions with respect to capital, labor, and materials are given by

$$MRPK_{si} = \left(\frac{\alpha_K}{\rho}\right)\left(\frac{P_{si}Y_{si}}{K_{si}}\right) = R\frac{1+\tau\mu(z_{si},\gamma)}{1+\mu(z_{si},\gamma)}\left(1+\mu(z_{si},\gamma)\right) \tag{18}$$

$$MRPL_{si} = \left(\frac{\alpha_L}{\rho}\right)\left(\frac{P_{si}Y_{si}}{L_{si}}\right) = w\left(1+\mu(z_{si},\gamma)\right) \tag{19}$$

$$MRPM_{si} = \left(\frac{\alpha_M}{\rho}\right)\left(\frac{P_{si}Y_{si}}{M_{si}}\right) = m\left(1+\mu(z_{si},\gamma)\right) \tag{20}$$

where $\rho = \frac{\sigma}{\sigma-1}$ denotes the constant markup of price over the marginal cost and $\mu(z_{si}, \gamma)$ denotes the multiplier on the credit constraint. $\mu(z_{si}, \gamma)$ plays the same role as τ_Y in the specification of Hsieh and Klenow (2009). Equations (18)–(20) show that firms with higher output distortions, or capital distortions, have higher marginal revenue products. According to Hseih and Klenow (2009), the after-tax marginal revenue products of inputs are equalized across firms, and the before-tax marginal revenue products of inputs must be higher in firms that have lower net worth, and can be lower in firms that have higher net worth. In my study, I compare the cases with and without credit constraints.

To determine the formula for industry productivity TFP_s, I measure the firm's TFPR ($TFPR_{si}$). By using equations (18)–(20), I can derive $TFPR_{si}$:

$$TFPR_{si} = \left(\frac{R}{\alpha_K}\right)^{\alpha_K}\left(\frac{w}{\alpha_L}\right)^{\alpha_L}\left(\frac{m}{\alpha_M}\right)^{\alpha_M}\left[\frac{1+\tau\mu(z_{si},\gamma)}{1+\mu(z_{si},\gamma)}\right]^{\alpha_K}\left(1+\mu(z_{si},\gamma)\right)$$

Firms with higher output distortions, or capital distortions, have higher marginal revenue products and consequently a higher $TFPR_{si}$. Following Hsieh and Klenow (2009), I can derive industry TFP_s as

$$TFP_s \;=\; \left[\sum_{i=1}^{M_s}\left(A_{si}\cdot\frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{21}$$

where $\overline{TFPR_s} = \frac{\sigma}{\sigma-1}\left(\frac{\overline{MRPK_s}}{\alpha_K}\right)^{\alpha_K}\left(\frac{\overline{MRPL_s}}{\alpha_L}\right)^{\alpha_L}\left(\frac{\overline{MRPM_s}}{\alpha_M}\right)^{\alpha_M}$ is the geometric average of the average MRPK, labor, and materials in the sector. If marginal products are equalized across firms, then $\overline{TFPR_s} = TFPR_{si}$, and consequently the efficient TFP_s^e would be

$$TFP_s^e = \bar{A}_s = \left[\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{22}$$

The gap between aggregate efficient TFP, denoted as TFP^e, and the actual level of TFP can be expressed as

$$\frac{TFP}{TFP^e} = \prod_{s=1}^{S}\left[\sum_{i=1}^{M_s}\left(\frac{A_{si}}{\bar{A}_s}\cdot\frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{\theta_s}{\sigma-1}} \tag{23}$$

This finding implies that capital misallocation due to the credit constraints arising from the asymmetric information between lenders and borrowers can lower aggregate TFP.

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