Financial Development and the Growth-Volatility Tradeoff: International Evidence*

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Abstract

We study how financial development affects the economy's growth-volatility profile in a large cross-section of countries. We construct a benchmark industrial composition as the set of sectoral allocations which minimize the economy's long-term volatility for a given level of long-term growth. We find that financial development increases substantially the speed with which the observed sectoral allocation of output converges towards the benchmark. We thus identify one channel through which financial development lowers aggregate volatility, namely, sectoral reallocation. Our results are robust to using various proxies for financial development, to accounting for the endogeneity of finance, and to controlling for investor's protection, contract enforcement, and barriers to entry.

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1 Introduction

What is the contribution of financial markets to the growth-volatility profile of a country's industrial output? Over the past two decades, a large empirical literature has documented the positive effect of financial development on long-term growth, both at the country and at the sector level.[1] At the same time, the direction and magnitude of the effect of finance on the volatility of output is still widely debated. Theoretically, financial intermediation can reduce output volatility if it alleviates firms' temporary cash flow problems (Caballero and Krishnamurty, 2001) or if it reduces the dependence of financial contracts on a borrower's net worth (Aghion et al., 1999). Alternatively, financial development can raise volatility by increasing the leverage of the typical firm, thereby making it more vulnerable to shocks (Kaminsky and Schmukler, 2008; and references therein). The empirical evidence is also inconclusive: while Easterly et al. (2000) find that a more developed financial system is associated with lower output volatility, Kaminsky and Reinhart (1999) document that crises are usually preceded by a sharp increase in the credit-to-GDP ratio, and Acemoglu et al. (2003) find that the effect of financial development on volatility disappears when institutions are accounted for.

More recently, Braun and Larrain (2005) and Raddatz (2006) have presented robust evidence that financial development lowers output volatility in manufacturing industries with high external dependence and liquidity needs. Estimating the effect of finance on volatility at the industry level is appealing as it addresses econometric problems endemic to cross-country studies, like left-out variable bias (both financial development and volatility could be driven by any of a long list of common omitted variables) and reverse causality (financial markets may predict lower volatility simply because they anticipate a decrease in future volatility). However, deriving conclusions about aggregate volatility from sector-level volatility requires questionable assumptions about the composition of output and the correlations across sectors. Therefore, it is still an open empirical

[1] See King and Levine (1993a), Rajan and Zingales (1998), Demirguc-Kunt and Maximovic (1998), and Beck et al. (2000) - among others - for seminal contributions, as well as Levine (2005) for a recent survey.

question whether financial development is Pareto-improving in a growth-volatility sense at the aggregate level.

This paper provides new evidence that the development of the financial system has a causal effect on the economy's growth-volatility profile. Specifically, we estimate the effect of finance on output growth and volatility by applying a methodology borrowed from mean-variance portfolio theory. Using data on sector-level value added for a wide cross section of countries over almost 40 years, we estimate the economy's long-term efficient frontier in the growth-volatility space. This allows us to construct, for each country, a benchmark set of sectoral weights which minimizes overall volatility for a given level of long-term growth. We then estimate how financial development (captured by the level of private credit to GDP) affects over time the speed with which the economy's actual industrial composition converges to the benchmark.

This approach has two appealing features. First, it provides a natural way to analyze growth and volatility patterns jointly. Second, it allows us to assess the overall reduction in aggregate volatility due to reallocation of output across sectors, as opposed to the reduction in aggregate volatility due to the reduction of sectoral volatility. In essence, this approach allows us to think simultaneously of the effect of financial development on sectoral reallocation and on optimal diversification.

We find robust evidence that developed financial markets are associated with a higher speed of convergence of the actual allocation of output across industrial sectors to the efficient benchmark in the dimension of lower volatility. A two standard deviation increase in financial development results in up to 3.5% higher annual speed of convergence towards a more diversified industrial composition. By means of illustration, if in 1970 Greece had as deep credit markets as the U.S., in 2007 its economy would have exhibited a diversification pattern associated with 18% lower volatility than the realized one.

The second contribution of this paper is to establish that the process during which financial development reduces overall volatility relies heavily on the cross-sectoral correlation mechanism. In fact, when in the construction of the efficient benchmark we set the correlations across industrial sectors to zero, the effect of financial development on the speed of convergence is substantially weakened. Our results thus imply that financial development does not reduce overall volatility by simply diverting investment towards low-volatility sectors. This result is fully consistent with the prior literature. For example, Wurgler (2000) argues that in financially developed economies, booming sectors generate higher investment and hence grow faster. To the degree that high-growth sectors tend to be high-volatility ones (Imbs, 2007), this would imply higher overall long-term volatility unless financial development decreases sectoral volatility, or unless correlations are at play. We confirm that in addition to the former, the latter is also the case.

As an illustration of how we think about optimality in a growth-volatility sense, our calculations suggest that a number of sectors have very small optimal weights, close to zero. For example, three sectors in the SIC 1-digit industrial classification (Agriculture, hunting, forestry and fishing; Mining and quarrying; and Construction) account for less than 5% of the share of output in the "optimal" sectoral portfolio implied by the long-term efficient frontier. Similarly, the actual share of manufacturing is higher than the optimal one by 14.5% on average, across countries and over time. At the same time, the sector Community, social and personal services accounts for 32.3% in the benchmark allocation. While agriculture and manufacturing are essential sectors, a large realized share of these two sectors implies an inefficiently diversified economy, given their long-term growth, volatility, and correlations with the returns in other sectors. We establish that financial development plays a Pareto-improving role by diverting resources away from such sub-optimally large sectors.

We address a number of concerns about the robustness of our main findings. First, our results might be capturing the demand-driven move over the development cycle towards sectors with lower intrinsic volatility, like health provision, education, and government services (Koren and Tenreyro, 2007). In that regard, an estimate of a positive effect of finance on convergence to the benchmark allocation might be biased by a preference-driven global move away from volatility. We address this concern by employing a panel specification with time, country, and industry fixed effects which allows us to isolate the contribution of the time-varying country-specific component of finance to convergence.

Second, our estimates may be contaminated by left-out variables bias and reversed causality. For example, unobserved entrepreneurial culture or households' propensity to save might be driving both output reallocation and financial development. Alternatively, if financial services are a superior good, richer and better diversified economies would have a higher demand for them. We address these concerns by first employing a cross-country cross-industry regression analysis *a la* Rajan and Zingales (1998) in which we include country and industry fixed effects. These fixed effects control for any potential feedback from the level of diversification to finance, as well as for the effect of omitted variables that affect diversification and vary by countries and industries. In some specifications, we also include country-industry dummy interactions, to sweep away the effect of time-invariant unobservables that vary by *both* country and industry. This strategy allows us to study the differential effect of financial markets on sectors that are naturally more responsive to finance. Second, we replace our volume measures of finance with data on liberalization events in financial markets. This *de jure* measure is largely exogenous (Bekaert et al., 2005) and so it should additionally address concerns about the endogeneity of financial development.

Third, in order to correct for the possibility that convergence is mainly driven by institutional factors, we allow our empirical procedure to account for some of the main legal and regulatory characteristics of the environment that might be correlated with financial development and thus bias our estimates. We also address concerns about the quality of our proxies for financial development. Finally, we test the hypothesis that a larger economic zone, like the euro zone, is a more suitable unit of observation than the country. Our main findings remain stubbornly robust to all these alternative specifications.

The rest of the paper is structured in the following way. Section 2 discusses related literature. Section 3 describes the construction of the optimally diversified benchmark, our empirical methodology, and the data. Section 4 presents the empirical results together with a battery of endogeneity and robustness tests. Section 5 concludes with a discussion of the main results and of possible extensions.

2 Related Literature

Our paper is related to several strands of research. A growing body of literature has focused on the link between economic growth and volatility of growth. From a theoretical point of view, the link is ambiguous. For example, endogenous growth is affected by business cycle volatility negatively in the presence of diminishing returns to investment, and positively in the presence of precautionary savings, creative destruction, liquidity constraints, or high-return high-risk technologies[2]. The combined evidence implies that growth and volatility tend to relate negatively at the country level (Ramey and Ramey, 1995), but positively at the industry level (Imbs, 2007). This apparent contradiction is resolved by noticing that the positive correlation between risk and return at the industry level is masked by aggregation, as aggregation only captures the covariance between sectoral growth and the country-specific component of aggregate variance, but not the sector-specific component of volatility. This approach of distinguishing between the country-specific and sector-specific elements of volatility is shared, among others, by Koren and Tenreyro (2007), who show that in large part the reduction of country-specific volatility over the development cycle is due to the reallocation of output to sectors with intrinsically lower volatility. We take the insight that individual industries exhibit growth-volatility patterns much like individual assets in a portfolio one step further by studying the diversification side of this argument and the contribution of financial markets to it.

At a general level, our paper also relates to the various contributions to the literature on finance and growth spurred by King and Levine (1993a,b)[3] that have looked at the effect on growth of credit markets (e.g., Rajan and Zingales, 1998; Beck et al., 2000; Beck and Levine, 2002; Fisman and Love, 2007), of equity markets (e.g., Levine and Zervos, 1998; Beck and Levine, 2004), and of financial

[2]See Imbs (2007) for an exposition of these arguments

[3]The idea to link finance and growth in a causal way is usually attributed to Schumpeter (1911), with later contributions by Goldsmith (1969) and McKinnon (1973).

liberalization (e.g., Bekaert et al., 2005; Bekaert et al., 2007), among others. This literature has generally found that financial development has a positive effect on the level of growth, especially in industrial sectors that rely on external finance and face higher growth opportunities. More relevant to our work, Wurgler (2000) brings evidence on the impact of finance on growth via the reallocation of output across industrial sectors. The main mechanism identified is that financial development increases long-term growth by reallocating investment from low-growth to high-growth sectors. Unlike our paper, this literature does not explicitly investigate how this growth-enhancing financial development process affects aggregate volatility.

A separate strand of literature has investigated the effect of financial intermediation on volatility independent of its growth impact. To begin with, theory has made ambiguous predictions on the direction of this effect. For example, Aghion et al. (1999) argue that a more developed financial system provides borrowers with tools to deal with information asymmetries arising in financial relations. Thus, financial development lowers the dependence of financial contracts on a borrower's net worth, reducing their role in the amplification of shocks. Similarly, Caballero and Krishnamurty (2001) argue that financial development lowers volatility by helping firms facing temporary cash flow or net worth problems to obtain the necessary working capital to finance their operations. At the same time, Hellman et al. (2000) argue that financial development fuels competition and erodes banks' franchise value, thus incentivizing banks to take on more risk. Since governments cannot commit not to provide bailouts in times of crises, banks have incentives to gamble for resurrection, exacerbating the business cycle. Finally, some authors argue that the effect of financial development on volatility is non-linear. For example, in a model with strategic complementarities and market imperfections, Carranza and Galdon-Sanchez (2004) show that the introduction of a financial technology positively affects the growth rate of the economy and at the same time is a source of higher variability, with most volatility events concentrated in low-income and high-income countries. The effect of finance on the variability of output is also expected to vary depending on whether monetary or real shocks are at play (Bachetta and Caminal, 2000) and on whether the real shocks are due to shifts in credit demand or in credit supply (Morgan et al., 2004).

Empirical work using various sample periods and proxies for financial development has presented evidence to both ends. For instance, Beck et al. (2006) have found that financial development lowers the volatility of output, while Kaminsky and Reinhart (1999) have found the opposite. In an attempt to resolve this controversy, Braun and Larrain (2005) and Raddatz (2006) both present evidence that financial development lowers output volatility in manufacturing industries with high external dependence and liquidity needs. They also argue that as long as industrial shares and the correlations of sectoral output remain constant, their results imply a reduction in overall volatility. In comparison, we explicitly allow for industrial shares and cross-sector correlations to evolve over time by observing the impact of financial development on the industrial composition of the economy over time, and we also estimate the concurrent effect of finance on growth.

Several recent contributions have aimed to study the effect of financial development on the growth-volatility profile of the economy in a more unified framework. For example, Levchenko et al. (2009) show that financial liberalization increases both the growth and volatility of output at the industry level. However, their conclusions about the effect of finance on aggregate volatility are based on the same strong assumptions about the composition of output and the correlations across sectors as Braun and Larrain (2005) and Raddatz (2006). Finally, in independent work Acharya et al. (2011) use the mean-variance efficiency framework we use here to show that branching deregulation in the U.S. has reduces state business cycle volatility through reallocation of output across sectors. Our approach differs in that we look at financial deepening rather than competition-ehnancing policies, and in that we look at the international dimensions of this effect in a large cross-sample of countries. Nevertheless, the results of both papers are in accord.

3 Methodology and Data

3.1 Constructing the Optimal Allocation Benchmark

We use the concept of mean-variance efficiency to define a benchmark industrial composition where output is allocated optimally across sectors in a growth-volatility sense. The idea is the following. A country's GDP is made up of the contributions of its industrial sectors. An individual economy's expected growth and volatility are therefore determined by:

1) its sectors' growth, volatility, and growth correlations;

2) its sectoral composition.

Thinking of a country's growth rate as the return on a portfolio, and its sectors as individual assets in that portfolio, we can construct mean-variance efficient frontiers *a la* Markowitz (1952) and compare them across countries. Each country's efficient frontier is composed of the set of minimum volatilities that can be achieved by optimally reallocating resources across sectors, for a given rate of growth.

Let $y_{c,s,t}$ be the rate of growth of sector s in country c at time t, and $w_{c,s,t}$ the corresponding sector's share of aggregate output. By construction, it must be that $\sum_{s=1}^{S} w_{c,s,t} = 1$ for all c and t, where S denotes the number of sectors. Each country's rate of growth $y_{c,t}$ can therefore be rewritten as:

$$y_{c,t} = \sum_{s=1}^{S} w_{c,s,t} y_{c,s,t} \tag{1}$$

Assuming that investors, citizens, and governments have preferences over growth and volatility, it is possible to find the optimal sector shares by maximizing a utility function which is increasing in return and decreasing in risk, in the same way an investor wishes to determine the utility maximizing portfolio from a given set of assets. Assuming a quadratic utility over growth and volatility, we can estimate expected utility as

$$\hat{U}_c(\mathbf{w}_c) = \hat{E}(\mathbf{w}_c'\mathbf{y}_{c,t}) - \lambda_c \hat{V}(\mathbf{w}_c'\mathbf{y}_{c,t}) \tag{2}$$

where λ_c is the risk aversion coefficient, $\hat{E}$ and $\hat{V}$ denote the estimated expected value and variance, and we format vectors in boldface.

In principle, it would be possible to compute a time-varying, conditional efficient frontier, for instance by modelling the variance covariance matrix with a multivariate GARCH model. However, since we are interested in the long-run growth and risk opportunities of the economy, it is more appropriate to use the unconditional means and variances. Both approaches rest on the implicit assumption that there are no structural breaks in the underlying stochastic process. Such an implicit assumption is common to the entire finance, growth and volatility literature.

For a given level of risk aversion, the optimal trade-off between growth and volatility is given by the solution to the following constrained optimization problem:

$$\left\| \begin{array}{ll} \max_{\mathbf{w}_c} \hat{U}_c(\mathbf{w}_c) & \\ s.t. & \mathbf{w}_c \geq 0 \\ & \sum_{s=1}^{S} w_{c,s} = 1 \end{array} \right. \tag{3}$$

The non-negativity constraint reflects the fact that in this context it is not economically meaningful to have negative weights for the industrial composition. The solution to such a problem requires the knowledge of the coefficient of risk aversion. As this is unknown, we modify the optimization problem as follows:

$$\left\| \begin{array}{ll} \min_{\mathbf{w}_{c,t}} \hat{V}(\mathbf{w}_{c,t}'\mathbf{y}_{c,t}) & \\ s.t. & \mathbf{w}_{c,t}'\hat{E}(\mathbf{y}_{c,t}) \geq \tilde{\mathbf{w}}_{c,t}'\hat{E}(\mathbf{y}_{c,t}) \\ & \mathbf{w}_{c,t} \geq 0 \\ & \sum_{s=1}^{S} w_{c,s,t} = 1 \end{array} \right. \tag{4}$$

where we denote with $\tilde{\mathbf{w}}_{c,t}$ the vector of observed weights for country c at time t. That is, we choose the point on the frontier which minimizes the country's output volatility for the realized level of growth. The distance between such a point and the actual levels of volatility can be interpreted as a measure of allocative efficiency, because it measures by how much a country could have reduced its macroeconomic volatility, while achieving the same level of growth, by simply allocating differently its resources across sectors.

Denoting the vector solution to this problem by $\mathbf{w}^*_{c,t}$, and by $w^*_{c,s,t}$ the individual elements of this vector, we can construct the following measures of country's allocative efficiency:

$$\begin{aligned} D_{c,t} &= \sqrt{\textstyle\sum_{s=1}^{S} \left(w^*_{c,s,t} - \tilde{w}_{c,s,t}\right)^2} = \left\|\mathbf{w}^*_{c,t} - \tilde{\mathbf{w}}_{c,t}\right\| \\ D_{c,s,t} &= \left|w^*_{c,s,t} - \tilde{w}_{c,s,t}\right| \end{aligned} \tag{5}$$

where $\tilde{\mathbf{w}}_{c,t}$ is the observed vector of actual allocations, and $\tilde{w}_{c,s,t}$ denotes its individual elements. Therefore, $D_{c,t}$ is the Euclidean distance between the optimal and actual vectors of weights, $\mathbf{w}^*_{c,t}$ and $\tilde{\mathbf{w}}_{c,t}$, while $D_{c,s,t}$ is the distance between optimal and actual weight for each component of those same vectors.

Figure 1 gives an illustration of how the actual allocation of industrial output over the sample period relates to the benchmark one for the U.S., the euro area, and Japan. Figures 2-4 illustrate the growth-volatility profile of several individual countries over the sample period. Clearly, while the U.S. has experienced a Pareto improvement in the sense of both lower volatility and higher growth, Japan has moved towards the frontier only in the dimension of growth, and Spain has actually experienced a divergence between 1990 and 2007, with higher growth rates achieved at the cost of higher volatility. These figures illustrates an important point: while countries mechanically converge in the growth dimension - as the relative weight of the fastest growing sectors increases over time - they may converge or diverge in the volatility dimension. To avoid the possibility that we are simply capturing a mechanical convergence in the growth dimension, the dependent variables in (5) measure the Euclidean distance between the weights associated with the actual and the corresponding efficient allocation along the volatility dimension.

3.2 Empirical Methodology

We study the link between finance and the economy's growth-volatility profile using a standard convergence framework. Our first convergence test estimates the degree to which distance for country c converges to the benchmark allocation following higher financial development. We estimate the convergence equation

$$D_{c,t} = \alpha D_{c,t-1} + \beta D_{c,t-1} \cdot Finance_{c,t} + \gamma Finance_{c,t} + \delta_c + \eta_t + \varepsilon_{c,t} \tag{6}$$

where $Finance_{c,t}$ is equal to a standard measure of financial market development, and $D_{c,t}$ is defined in Equation (5).[4] Our coefficient of interest is β: if $\beta < 0$, then greater financial development is associated with faster convergence to the benchmark allocation.[5] The inclusion of country and year fixed effects allows us to purge our estimates from the effect of unobservable global trends (like the "Great Moderation") and unobservable country-specific time-invariant institutional influences, and isolate the within-country effect of financial development.

The relationship between financial market size and the economy's growth-volatility profile is illustrated in Figure 5, which plots each individual country's autoregressive annual speed of convergence to the benchmark industrial allocation over the sample period (calculated using data at the 2-digit level of disaggregation) against initial ratio of private credit to GDP, for the cross section of OECD countries.[6] Clearly, the correlation is strongly positive. Countries with initially deeper

[4] It's important to note that equation (6) can be rewritten as

$$D_{c,t} = \alpha D_{c,t-1} + (\beta D_{c,t-1} + \gamma) \cdot Finance_{c,t} + \delta_c + \eta_t + \varepsilon_{c,t}$$

and so the full effect of finance on distance to the allocative efficiency frontier is given by $\beta D_{c,t-1} + \gamma$. For example, if both β and γ are negative, then more finance decreses distance to frontier, but if $\beta < 0$ and $\gamma > 0$, then the total effect of finance depends on $D_{c,t-1}$, and for low levels of $D_{c,t-1}$, finance could lead to divergence even if $\beta < 0$.

[5] As pointed out by Acharya et al. (2011), the frontier is estimated with an error, and hence there is an attenuation bias in estimating convergence. This works against finding an effect and hence what we see in the data should be interpreted as a lower bound for the true effect. In addition, as shown by Jagannathan and Ma (2003) in the context of mean-variance allocation, imposing non-negative constraints significantly reduces the impact of estimation error.

[6] We define the autoregressive annual speed of convergence as $1 - \alpha_c$, where α_c denotes the estimate from the regression

$$D_{c,t} = \alpha_c D_{c,t-1} + \varepsilon_{c,t}$$

credit markets - typically Anglo-Saxon - experienced a larger annual reduction in distance to the optimally diversified benchmark over the past 40 years than less financially developed countries (typically Mediterranean and transition economies). 12% of the cross-country variation in the speed of convergence to the benchmark industrial allocation is explained by the size of financial markets.

Next, we perform the same test on the country-sector level disaggregated data, and define $D_{c,s,t}$ as in Equation (5) above. This allows us to directly look into the issue of reallocation and examine which sectors move faster to their implied optimal weights following financial development. Formally, we estimate the convergence equation

$$D_{c,s,t} = \alpha D_{c,s,t-1} + \beta D_{c,s,t-1} \cdot Finance_{c,t} + \gamma Finance_{c,t} + \delta_c \cdot \phi_s + \eta_t + \varepsilon_{c,s,t} \qquad (7)$$

As in the previous specification, the inclusion of country, sector, and year fixed effects allow us to purge our estimates from the effect of unobservable global trends and unobservable industry and institutional influences, and isolate the within-country-by-sector effect of financial development. Equation (7) estimates whether financial development accelerates the reallocation across sectors within a country in the direction of the implied optimal sectoral shares in this country. In comparison, while Equation (6) is a test of convergence of country-level aggregates towards the optimal benchmark, Equation (7) estimates reallocation across sectors in the direction of the optimal weights.

We address the issue of the endogeneity of financial development in two alternative ways. First, we replace our volume measures of finance with dummies equal to 1 after the year in which domestic financial markets were liberalized. It is commonly believed that policy decisions are more exogenous than volume measures of finance (Bekaert et al., 2005). Second, we employ the Rajan and Zingales (1998) approach of interacting our measure of finance with a measure of each sector's natural characteristic, in this case, long-term industry-level benchmark Sharpe ratio, and benchmark share

for each country c in the sample.

of small/young firms. By identifying one channel via which finance should speed convergence - that is, more so for sectors which naturally offer lower risk for the same level of return, and which are naturally more sensitive to external finance - we aim to purge the possible bias in our estimates induced by simultaneity.

Finally, we repeat our main exercise on aggregate euro zone data for the 1991-2007 period (due to the unification of Germany in 1991, prior data cannot be used). This gives us two additional insights. First, it allows us to ask whether the effect of finance on convergence holds in larger economic zones, given that a country might not be the most suitable unit of observation when studying diversification and allocation across industrial sectors. For example, Krugman (1991) points out that demand linkages and costly trade will rather lead to sectoral specialization not within one U.S. state, but between, for example, the East Coast and the U.S. mainland. The European analog of this argument would be differences in specialization patterns between the industrialized North and the agricultural South. Second, it allows us to instrument euro zone credit with an indicator variable equal to 1 after 1999, the year of the introduction of the euro. While the euro might not be such a good instrument for credit market development because it may also affect convergence through increased trade and reduced exchange rate risk, this exercise still allows us to address the endogeneity of financial market development from another angle.

3.3 Data

Our main data on nominal value added - which we deflate to get real values - come from the STAN Database for Structural Analysis and cover 28 countries over the period 1970-2007[7]. The data are decomposed alternatively into 9 SIC 1-digit and 20 SIC 2-digit sectors. While it would seem natural to only focus on the finer disaggregation, as with 9 industries we lose substantial sectoral variation, disaggregating the data by SIC 1-digit industries serves two important purposes. For one, we thus make sure that we do not include sectors with negligible output share in the calculation

[7] For 6 countries - Czech Republic, Germany, Hungary, Poland, Slovakia, and Switzerland - coverage only starts in the early 1990s - see Table 1 for details.

of the benchmark allocation of output across sectors. Second, given the dimensionality restrictions involved, we are unable to construct benchmark output allocations for countries for which data start after 1987 if we only have the set of 20 2-digit industries. It is also worth noting that if anything, aggregation into a set of so coarsely defined industrial sectors makes it harder rather than easier to detect an effect of finance on the reallocation of resources across economic activities.

Two data clarifications are in order. First, disaggregated data tend to be arbitrary in the sense that some economic activities are classified more coarsely than others. If data on one type of economic activity are consistently collected in a more disaggregated fashion, convergence to the mean-variance efficiency frontier may emerge as a mechanical property of that process (Acharya et al., 2011). We address this issue by employing data at different levels of disaggregation; however, given the dimensionality limitation imposed in calculating the mean-variance efficiency frontier, which requires that the number of years in the data exceeds the number of sectors, we resort to using the data at the SIC 1-digit and OECD 2-digit aggregation. Second, while the UNIDO has been the preferred dataset in the finance and growth literature, it only includes data on the manufacturing sector, and so STAN is more suited to studying optimal reallocation in the context of the major shift during the sample period from manufacturing towards services, for example.

The financial variables used in this paper come from two different sources. The main measure of financial markets development is PRIVATE CREDIT / GDP. What goes into the numerator is the value of total credits by financial intermediaries to the private sector (lines 22d and 42d in the International Financial Statistics), and so this measure excludes credits issued by the central banks. The reason for this exclusion is that in many cases it is likely to be determined by political rather than economic considerations. It also excludes credit to the public sector and cross claims of one group of intermediaries on another. Finally, it counts credit from all financial institutions rather than only deposit money banks. The data on this variable come from Beck et al. (2010) and are available for all 28 countries in the data set between 1970 and 2007.

While the main measure of domestic financial development considered in the paper is ubiquitous in empirical research, it is intrinsically likely to contain measurement error. For one, it is difficult to capture all aspects of financial development in one empirical proxy. Second, there are idiosyncratic differences across countries in the availability of unobservable sources of working capital, such as trade credit or family ownership. To confront these issues, we use in robustness tests data on equity market size (STOCK MARKET CAPITALIZATION / GDP), bond market size (PRIVATE + PUBLIC BOND CAPITALIZATION / GDP), as well as various measures of financial integration.

We also address the issue of the endogeneity of any volume measure of finance to economic development by employing a *de jure* measure of financial development in addition to the *de facto* one. In practice, we replace PRIVATE CREDIT / GDP with information on banking sector liberalization dates. This alternative indicator is constructed by assigning a value of 0 for the years in which the country's domestic credit market was not liberalized, and 1 for the years after it became liberalized. The indicator comes from Bekaert et al. (2005).

Table 1 summarizes the sectoral data, for both the SIC 1-digit and the OECD 2-digit classification used, along with initial date for which the sectoral data are available. Table 2 summarizes the data on both the *de facto* and the *de jure* measures of credit market development.

4 Empirical Results

This section is split into four subsections. The first (4.1) investigates the effect of finance on the economy's growth-volatility profile. The second (4.2) addresses various simultaneity issues associated with faster convergence to the benchmark allocation of output. The third (4.3) studies the importance of reallocation across sectors in the process of convergence towards the benchmark. The fourth (4.4) studies whether the main findings are affected by accounting for other characteristics of the business environment, by the choice of proxy for financial development, and by the choice of unit of observation.

4.1 Finance, Growth, and Volatility

The first empirical question addressed in this paper is whether finance accelerates the country's convergence to the benchmark allocation of industrial output implied by sectoral long-term growth, volatility of growth, and growth correlations across sectors. We study this effect in Panel A of Table 3. Columns (1) and (3) report the estimates of Equation (6) for the 1- and 2-digit data, respectively. Only the countries for which the time dimesion of the data is at least as large as the sectoral dimension are used to calculate distances to frontier; for the rest the variance-covariance matrix is singular.[8] The estimate of the direct auto-regressive coefficient on distance to frontier so defined, α, implies a yearly reduction of between 5.5% and 9.5% in our sample. Importantly, the effect of finance interacts negatively with distance as implied by the estimate of the coefficient β. Therefore, our estimates suggest that financial development has a positive effect on the speed with which countries converge to their efficiency frontier. Numerically, a two-standard deviation increase in financial development results in a speed of convergence to the frontier by higher by about 3.5% annually. The magnitudes of the effect are roughly similar across 1-digit and 2-digit disaggregation of the data, and equally significant.

One immediate caveat is that the benchmark allocation of output itself may have been affected by financial development. If finance affects both growth and volatility, as the literature on finance and growth has argued, then initial financial underdevelopment will result in artificially low early growth and high early volatility. Structural breaks in financial development, therefore, will remove constraints to growth and lower volatility, and that would effectively contaminate our long-term benchmark. One solution is to calculate a "clean" frontier in which long-term growth, volatility, and growth correlations have not been affected by finance mid-cycle. In Columns (2) and (4) we do so by estimating Equation (6) on a restricted sample of countries which liberalized domestic credit markets before the beginning of the sample period. In that way we make sure that we are measuring convergence to an allocative efficiency benchmark based on unconstrained long-term

[8] This results in the exclusion of the Czech Republic, Germany, Hungary, Poland, Slovakia, and Switzerland from the exercise on the 2-digit data, as for all 6 countries there are less than 20 years of data available.

growth and volatility, and not to one contaminated by the initial underdevelopment of financial markets. The statistical significance of our estimates remains unchanged, and the economic meaning of the coefficients is if anything higher than implied by the estimates on the full sample.

We next use the disaggregated nature of our data to study the effect of finance on the difference between actual and optimal output shares for each country-sector. This procedure is aimed at giving us a better idea of which sectors are primarily responsible for the speed of the convergence to a country-wide allocative efficiency frontier. For a start, we find that 6 sectors in the SIC 1-digit industrial classification account for 95% of the share of output in the "optimal" sectoral portfolio implied by long-term growth and volatility of growth. The sectors with the biggest weight in the optimal portfolio are Community, social and personal services (32.3% in the SIC 1-digit case); Finance, insurance, real estate and business services (26.7% in the SIC 1-digit case); and Transport, storage and communication (14% in the SIC 1-digit case). The former two sectors of the last group also exhibit the biggest difference between actual and optimal share, 21.4% and 18.5% on average across countries and time, with their optimal share being higher than their actual one. On the other side of the spectrum, our estimates imply that on average, the actual share of manufacturing is higher than the optimal one by 14.5%. This suggests that in a sample of industrialized countries at least, there is "too much" manufacturing across the board given the optimal share of manufacturing implied by our benchmark calculations.

Panel B of Table 3 reports the estimates of Equation (7). We essentially repeat the same procedure from the country tests: in Columns (1) and (3), we use the full sample of countries, and in Columns (2) and (4) we exclude countries which liberalized domestic credit markets during the sample period. The regressions include time dummies to account for shifts associated with global unobservables, like the "Great moderation", for example. They also include a set of country-industry interaction dummies to account for the fact that low-volatility sectors may be a superior good (Koren and Tenreyro, 2007). The effect of private credit on convergence survives the disaggregation. In this specification, we estimate that a two standard deviation increase in our proxy for financial market development accelerates the speed of convergence by about 1.5% annually.

In Table 4 we repeat the empirical exercises from Table 3 using a GMM Arellano-Bond (1991) estimator rather than a OLS procedure. We do so in order to account for the presence of a lagged dependent variable in dynamic panel data. In unreported regressions, we also estimate the GMM estimator introduced by Blundell and Bond (1998) which corrects for the bias arising in fixed effects estimations in dynamic models. This correction is standard in panel estimation of the finance and growth nexus (e.g., Acharya et al., 2011; Bonfiglioli, 2008). Our results continue to hold.

In all, Tables 3 and 4 imply that part of the effect of finance is a re-structuring of output away from sectors with low optimal and high actual weight towards sectors with high optimal and low actual weight. This might be happening because the former have a negative long-term Sharpe ratio and so have to gradually disappear from an efficient portfolio. Hence, we partially capture the effect of finance on the natural disappearance of obsolete sectors. In theory it could be that the total effect depends on initial conditions, and so the overall effect of finance is confounded by a very inefficient initial sectoral allocation, limiting the effect of diversification as in Acemoglu and Zilibotti (1997). The effect of finance could also be confounded by other political economy forces, for instance, large inefficient sectors might be using lobbying tools to acquire government resources and continue existing while their implied weight might be zero. We investigate these possibilities later on.

It is important to point out that finance has a direct positive and statistically significant effect on the distance (for example, estimate of 0.002 in Column 1 of Table 3, Panel B). This implies that close to the frontier, more finance is associated with a divergence rather than convergence to the frontier.[9]

[9] However, that point is quite close to the frontier. For example, for the sample mean value of private credit to GDP, the distance beyond which more finance leads to divergence is 0.0024 in the MVE metric, a value attained by 1.7% of the country-sector-time observations in our sample.

4.2 Addressing the Endogeneity of Finance

We have so far established a positive correlation between financial development and convergence to a benchmark allocation of industrial output defined in the sense of mean-variance efficiency. However, the question of causality has been left largely unanswered. Given the evidence so far, the argument can still be made that financial development has simply increased in the wake of faster diversification, in itself driven by factors unobservable to the econometrician. For example, the observed pattern could be due to the fact that more optimally diversified economies consist of large capital-intensive sector, and so a large financial industry emerges to serve those. Alternatively, unobservable factors like the propensity to save might be driving both the size of financial markets and diversification patterns. In this subsection, we describe how we deal with these issues.

4.2.1 The Nature of Reallocation

We first address the issue of omitted variable bias by employing the methodology first introduced by Rajan and Zingales (1998). They document the significance of the interaction term between a country-level characteristic of financial development and an industry-level characteristic of financial dependence. The innovation of the method is in that they use a U.S. benchmark to construct an exogenous measure of financial dependence in their sample of countries which excludes the U.S. This empirical strategy alleviates concerns about the ability of financial development to anticipate growth. It also addresses questions about the joint determination of financial development and growth by a third, unobservable factor.

One natural channel via which we expect finance to exert a causal effect on convergence to frontier is the technological risk-adjusted growth of the sector. Movement towards the frontier is associated with an increase in the Sharpe ratio[10] of the portfolio via reduction of volatility for the same level of return, or alternatively, an increase in return for the same level of volatility. Financial markets are looking for the best investment opportunities in terms of risk-adjusted growth. There-

[10] The Sharpe ratio is defined as the sector's long-term growth rate divided by the standard deviation of the sector's long-term growth rate.

fore, the effect of financial development on sectoral reallocation within the portfolio of industrial sectors should work faster for those sectors that exhibit the highest Sharpe ratio for technological reasons. For instance, if the communications sector offers the lowest volatility for the same return, then finance will be expected to reallocate resources towards that sector faster than for sectors with lower Sharpe ratio (controlling for cross-sectoral growth correlations and for initial distance).[11]

Another sectoral characteristic, exploited widely in related literature, is a sector's natural dependence on external finance. If financial underdevelopment affects the allocation of output across business activities, that limitation will likely be most severe in sectors which naturally rely on external finance. Such sectors will likely have a high share of small as well as young firms (e.g., Aghion et al., 2007; Acharya et al., 2011). The share of small/young firms will therefore be a good proxy for the natural external finance need of the sector.

We investigate this channel in Table 5. Of course, using the sectors' country-specific Sharpe ratios and share of young/small firms would make the estimation prone to the same endogeneity concerns as before. For that reason, we follow Rajan and Zingales (1998) and compute the Sharpe ratio for each of the 9 SIC 1-digit sectors and 20 OECD 2-digit sectors in the U.S. In addition, we instrument the U.S. industry-level Sharpe ratio with the predicted sample one interacted with U.S. average financial development (Ciccone and Papaioanou, 2006). This gives a measure of what the median sample risk-adjusted growth would be if it was observed in a country with the U.S. level of financial development. This approach addresses one of the main criticisms against the Rajan and Zingales methodology, namely that it uses a benchmark extracted from a specific industrial composition and thus a noisy measure of "true" risk-adjusted growth. Regarding the share of young firms, we calculate it for each sector using data from the Dun and Bradstreet database, averaged for the 1985-1995 period, and again instrument it for with the sample measure of that share, using data from Amadeus, interacted with the U.S. measure of financial development. Then, we interact these two industry benchmarks with the interaction term in Equation (7), and exclude the U.S.

[11] The idea is similar to Wurgler (2000). However, he looks at growth only and doesn't take into account the growth volatility of the sectors.

from the regressions that follow.

The estimates confirm the effect that we already found in Tables 3 and 4 when we use the industries' "natural" long-term Sharpe ratios, for data at the 1-digit (Column (1)) and 2-digit (Column (3)) level of disaggregation. Namely, financial development as proxied by PRIVATE CREDIT / GDP increases the speed with which sectors' shares converge to the benchmark implied by mean-variance efficiency, and this effect is stronger for sectors that naturally have higher Sharpe ratios. The exact same results are obtained when we differentiate by the share of young firms (Column (2) for 1-digit and Column (4) for 2-digit data): sectors with a higher share of young firms (presumably, sectors with higher natural information frictions, which finance should affects more strongly) see a faster reallocation following financial development.

It should be noted that each sector's benchmark Sharpe ratio is measured for the same time period used for the sample countries - namely, a full 38 years. The first reason for doing so is that we want to calculate "natural" volatility over a relatively long period of time. The second reason is that we think of the US benchmark over the 1970-2007 period as a global ex-ante one given the technological opportunities of that sector. Then the question becomes one of how financial development affects sectoral reallocation given the *potential long-term* performance of the countries' sectors.

4.2.2 Reversed Causality

We now proceed to address the issue of reversed causality. For example, countries that diversify faster may demand larger financial sectors if they derive a larger share of economic output derives from more capital intensive industries. For that reason, in Table 6, we account for the endogeneity of finance in an alternative fashion. Namely, we replace our preferred measure of financial development with liberalization dates of domestic credit markets, as per Table 2. We do so both for sectoral data at the 1-digit (Column (1)) and 2-digit (Column (3)) level of disaggregation. Although the argument has sometimes been made that liberalization may be endogenous as policy makers may be undertaking it at the times when the country is starting on the path of higher growth[12], a policy measure is more exogenous to growth opportunities than the volumes measures we have used so far. Hence, we replace the financial proxy in Equation (7) with a dummy variable equal to 1 after the year in the country liberalized its credit markets. We continue to measure a positive effect of credit markets on the speed of convergence.[13]

Another issue with our tests so far is that the financial sector is included both in the left-hand side and the right-hand side of the estimation equation. To address this concern, in Columns (2) and (4) of Table 6 we exclude the sector "Finance, insurance, real estate and business services" and "Financial intermediation" from the main tests using the data disaggregated at the SIC 1-digit and the OECD 2-digit level, respectively. As explained before, our previous results might be biased by the fact that the proxies for financial development we use increase simultaneously alongside the share of financial services on the left-hand side. The effect of credit market development, however, survives this procedure, with a largely undiminished magnitude.

Taken together, these tests point to the fact that the endogeneity of the volume measures of finance used so far may be inducing attenuation bias in our estimations, while the inclusion of the financial sector may be biasing the results upwards. In all, our measure of credit markets development continues to affect strongly the speed of convergence to the benchmark output allocation in all tests.

4.3 Optimal vs. "Naive" Diversification

The virtue of our benchmark allocation of industrial output, based on the concept of mean-variance efficiency, is that it accounts simultaneously for sectoral growth, volatility, and cross-correlations. We now contrast our results with those obtained by assuming away the importance of cross-sector correlations, or of sectoral growth, volatility, and correlations. In the first case, we estimate a

[12] See Bekaert et al. (2007) for details.

[13] This result is reminiscent of Bekaert et al. (2007) who find that an exogenous measure of growth opportunities predicts faster growth than the endogenous one.

benchmark frontier in which all covariance terms are set to zero. This transforms a mean-variance efficiency argument into one in which finance targets sectors based solely on their individual Sharpe ratios. Such a framework fails to explain the full pattern of convergence of sector weights in country-level value added (Table 7, Column (1) of Panels A and B). This implies that the effect of finance on diversification is significant only when the covariance of returns is properly accounted for in an optimal portfolio sense. This point is relatively important: our results show that financiald evelopment results in lower aggregate volatility not just through a reduction in intra-sectoral volatility as in Braun and Larrain (2005) and Raddatz (2006), but also through a reallocation of resources away from sectors whose growth pattern is highly correlated with the growth pattern of the rest of the economy.

Similarly, we contrast our measure of diversification based on allocative efficiency with measures which define diversification as an equal spreading of output across industrial sectors. One such "naive" measure is the Ogive index which is widely used in studies of geographic diversification (e.g., Conroy, 1975). For a set of $i = 1, ..., n$ individual sectors with corresponding shares s_i, the Ogive index is calculated as $n \sum_{i=1}^{n} \left(s_i - \frac{1}{n}\right)^2$. A second such natural measure is the Herfindahl-Hirschman index defined as $\sum_{i=1}^{n} s_i^2$. A third one is the Gini coefficient, defined as $\frac{1}{2n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} |s_i - s_j|$.[14] All measures are identical in the sense that they constitute a "naive" concept of diversification which ignores any considerations about growth, volatility, and cross-sector correlations.

Columns (2)-(4) of Table 7, Panels A and B, report the results of a set of tests in which the original measure of distance to our diversification benchmark is replaced with each of the "naive" measures of diversification just defined (which can also be understood as distance to an "absolute" diversification benchmark, as all three mechanical measures assign a value of 0 to equally spread output, and a value of 1 to output concentrated in one sector). The results suggest that finance has no significant effect on the speed with which the country allocation of output converges to a benchmark in which output is equally spread across the set of industrial sectors available. And

[14] See Imbs and Wacziarg (2003) for details on implementation.

while the coefficient on the measure of diversification implies that diversification increases over time, it does so at a much lower speed than our measure of allocative efficiency, and in the case of the Gini coefficient, for example, convergence is almost nonexistent.

One immediate intepretation for this result is in the spirit of the U-shaped diversification pattern over the development path documented by Imbs and Wacziarg (2003). Our finding that for a set of industrialized economies, output is spread as to minimize overall growth-adjusted volatility is not inconsistent with a development pattern in whose later stages the economy specializes in order to exploit pecuniary externalities and economies of scale. At the same time, that economies with more efficient financial markets do not exhibit a more equal spreading of output across sectors is also consistent with a development path in which "naive" diversification does not evolve linearly over time.

4.4 Robustness

Our empirical methodology so far has been very parsimonious: we have studied the effect of finance on the speed of convergence, accounting for natural convergence, global time trends, and country-industry unobservables. We have also addressed various sumulteneity concern to strengthen the causality argument, and shown that finance exhibits no effect on "naive" measures of diversification which ignore the interplay of growth and volatility at the sectoral level. In this section, we perform additional robustness checks addressing the quality of our financial development proxies, alternative characteristics of the business environment, and alternative units of observation.

4.4.1 Alternative Measures of Financial Development

So far we have relied exclusively on the time series of the ratio of private credit to GDP to capture the country-specific evolution in financial depth. Given the importance of access to increasingly international capital markets, especially for some industrial sectors, alternative measures of financial development that capture the international supply of capital beg to be considered. In the first two columns of Table 8, we replace our proxy for financial depth with measures of stock and bond market capitalization to GDP. (For the sake of brevity, we do so only for country-industry distances to our benchmark allocation of industrial output across sectors). The results are somewhat less consistent than in the case of credit markets. When we calculate the benchmark allocation of output across sectors using 20 2-digit industries (Panel B), both deeper stock market and deeper bond markets turn out to be associated with faster convergence to the benchmark (Columns (1) and (2)). However, when we use the 9 1-digit industries to calculate the benchmark, the results are no longer significant. Nevertheless, these findings are broadly in line with the growth effects in Rajan and Zingales (1998) and the volatility results in Braun and Larrain (2005), suggesting that there is nothing peculiar about credit market depth as a measure of financial development.

Next, we pay explicit attention to the fact that countries can also diversify abroad, both in terms of direct and portfolio investment, and this is likely to be especially important for small, open economies. While we have made it impossible for economies to "short" a sector by construction, we can still look at the financial side of cross-border diversification. In Columns (3)-(4) of Table 8, we control for trade openness (using the ratio of exports plus imports to GDP), for integration in international financial markets (by using the ratio of total foreign assets and liabilities to GDP), and for the share of net foreign assets to GDP in the country. All of these alternative measures of finance turn out to be significant in at least one specification and level of data disaggregation, and the sign of the estimates implies that they affect convergence in the same direction as credit market development. One can therefore confirm that measures of financial depth seem to affect the speed of convergence to allocative efficiency frontier alongside measures of international financial integration.

Finally, our data allow us to pay specific attention to financial services as a productive sector of the economy. In particular, some countries may have a comparative advantage in financial services due to specialization in a particular type of human capital, or due to early specialization in banking activities. One way to exploit this possibility is to test whether countries with initially relatively large financial sectors have different diversification paths than countries with initially relatively small financial sectors. We perform our main tests on these two sub-samples of countries, and report the results in Columns (5) and (6). The estimates imply that deeper financial markets speed up convergence to allocative efficiency frontier for both types of countries, however, the gain in speed of convergence is relatively higher for countries which initially specialized to a lower degree in financial services.

4.4.2 Finance, Law, and Regulation

Another important issue to address is that finance may simply be proxying for other characteristics of the business environment. In particular, GDP growth rates tend to be positively related to a wide array of institutional factors which tend to be correlated. For example, financially more developed countries tend to have better institutions, less rigid regulation of businesses, and better protection of investors and enforcement of contracts. To the extent that the degree of development tends to be similar across most dimensions of financial, regulatory, and legal development, those could all be capturing similar aspects of a favorable business environment. We therefore consider the effects of barriers to entry, investor protection, and contract enforcement on convergence to the benchmark allocation of industrial output.

The reason we focus on these three dimensions of the business environment is that they have been found to explain variations in industry growth in previous studies. For example, Klapper et al. (2006) show that entry barriers are associated with lower firm entry in industries characterized by higher business churn. Entry barriers could thus result in slower convergence to the benchmark allocation of industrial output if the industries with the highest optimal share are the naturally highest-entry ones. Djankov et al. (2008) show that a stricter enforcement of minority shareholders' rights results in a more dynamic economy, as measured by the number of active firms per population. To the extent that the number of active firms is a proxy for the optimal utilization of growth opportunities, low degree of investment protection may be hampering convergence to the benchmark allocation of industrial output by constraining industry growth. Finally, insufficient contract enforcement is argued to have been the main culprit in various countries' observed long-term decline (e.g., Clague et al., 1999).

In Table 9, we repeat our previous estimations at the country and country-industry level in a horse race in which interactions of last period's distance to the benchmark allocation of industrial output with the respective characteristic of the business environment have been included in the model. Data on entry barriers (number of days it takes to register a new business), investor protection (composite of transparency of transactions, liability for self-dealing, and shareholders' ability to sue officers and directors for misconduct), and contract enforcement (number of days it takes to resolve a contractual dispute in court) come from the Doing Business Database of the World Bank, and are averaged over the longest available period. We perform the analysis both at the country (Panel A) and industry (Panel B) level, as well as both on the 1-digit (Columns (1) and (2)) and 2-digit (Columns (3) and (4)) data. We find that industries converge more slowly to their optimal share in countries where it takes longer to register a business. We also find that better investor protection accelerates convergence to frontier. Finally, convergence is slower in countries where it takes longer to resolve contractual disagreements. The sum of these results suggests that legal and regulatory obstacles can slow down convergence to an allocative efficiency frontier - for example, by increasing the marginal cost of investing in opaque high-growth sectors. Importantly, the effect of finance we observed in previous regressions survives this robustness exercise. It also holds when we exclude the countries which liberalized domestic credit markets during the sample period which may have induced a structural break in the benchmark industrial allocation (Columns (2) and (4)).

4.4.3 Stages of Diversification

In Table 10, we test how financial depth affects the allocation of industrial output across sectors for different initial stages of diversification. Imbs and Wacziarg (2003) show that diversification follows a non-linear pattern over the development cycle, so it is conceivable that our benchmark allocation of output will be affected by finance differently at various stages of diversification. We split the countries in subgroups based on initially "low" vs. "high" degree of diversification (essentially - the bottom vs. top half of the distribution of initial distances to our benchmark industrial allocation). Then, we test how financial market development affects the speed of convergence for different degrees of initial diversification. While it is tempting to hypothesize that bank credit is more important at intermediate stages of diversification, whereas access to equity markets is more important for advanced stages of diversification, we find that bank credit tends to matter for convergence to the benchmark industrial allocation at all stages of diversification, and access to equity markets matters mostly for countries with low initial degree of diversification. The former result is consistent with Larrain (2005) who argues that bank credit is monotonically related to output smoothing, while the latter is consistent with a general argument that developed equity markets are particularly relevant for risk sharing (e.g., Bekaert et al., 2006; Henry, 2000).

4.4.4 Finance and Diversification: Larger Economic Zones

One final critical question to our approach is whether a national economy is a proper unit of observation. The literature on the geographic agglomeration of economic activity, pioneered by Krugman (1991), points out that demand linkages and costly trade will rather lead to sectoral specialization not within one U.S. state, but between, for example, the East Coast and the U.S. mainland. Kalemli-Ozcan et al. (2010) also emphasize that the euro area might be a more appropriate unit of observation to study intersectoral allocation than an individual euro area member country. In that sense, that the German region of Bavaria specializes in car production and the German region of Rhineland specializes in wine production might be less important than the fact that Germany has a relatively large automobile industry while Portugal has a relatively large wine industry.

Our framework allows for an immediate test of this hypothesis. In Table 11, we report the estimates from revised versions of previous regressions where we have calculated distance to the benchmark allocation of industrial output using aggregate sectoral data for the euro area starting in 1991[15], and our main measure of finance is now the aggregate credit-to-GDP ratio for all euro area countries for each year starting in 1991. Given that we only have 17 years of observations, we only use disaggregation at the 1-digit SIC industry level to calculate the efficiet frontier. Across the board of empirical tests, we confirm that deeper credit markets are associated with a faster convergence to an allocative efficiency frontier. As before, we use OLS and a GMM procedures (Columns (1) and (2), respectively), we account for "natural" industry characteristics, like information frictions and "natural" risk-adjusted growth (Columns (3) and (4), respectively), and we exclude the financial sector from the exercises (Column (5)). We also use the introduction of the euro in 1999 as an instrument for financial development (Column (6)). While the validity restriction is undoubtedly satisfied, the argument can be made that the introduction of the euro in 1999 may have shifted the frontier by allowing faster reallocation along other dimensions, like trade and the reduction of exchange rate risk, which invalidates the exclusion restriction. Therefore, this final test should be interpreted with caution.

5 Conclusion

This paper investigates the effect of financial development on the economy's growth-volatility profile for a wide cross-section of countries. We document two main findings. First, financial development is Pareto-improving in the sense of delivering lower aggregate long-term volatility for the same level of long-term growth. Second, the reduction in aggregate volatility is realized through a reallocation of resources towards sectors with higher "natural" Sharpe ratios and sectors whose growth profile exhibits low correlation with the rest of the economy. Thus, we identify another channel through which financial development affects aggregate volatility, in addition to reducing the sectors' own long-term volatility. While we document this general result for a variety of empirical proxies for

[15]The unification in 1991 of the largest economy in the euro zone, Germany, makes it impossible to use pre-1991 data.

financial development, credit market development seems to have the most consistently significant effect.

Crucially, our findings do not seem to be driven by a global demand-driven shift away from volatile industrial sectors, by the endogeneity of financial development, by the usage of an inappropriate economic unit (a domestic economy), or by other institutional developments that financial development could merely be a proxy of. In particular, our results survive panel regressions with a rich set of fixed effects, and they are not weakened when we use exogenous measures of financial development, like deregulation, or when we investigate the effect of financial development on the growth-volatility profile of a larger and potentially more relevant economic unit, like the euro area. Finally, while regulatory and legal institutions also contribute to the process of convergence to our benchmark allocation of industrial output, they do so without diminishing the independent role of finance.

Our main contribution lies in showing that following financial development, reallocation effects have largely contributed to the overall global reduction in volatility in the past several decades. In addition, we provide a natural way to think about the *simultaneous* effect of financial development on growth and volatility. While in independent work Acharya et al. (2011) show similar effects from banking deregulation in the U.S., we present evidence that a Pareto-improvement in a growth-volatility sense is not a feature of a particular country or a particular policy event, but an empirical regularity in a cross-country setting. Nevertheless, we stop short of a number of important extensions. To name just one, our sample only consists of industrialized countries due to the data limitations imposed. Unlike standard cross-country cross-industry studies, which use data on manufacturing output for both developed and developing countries, our methodology requires output data for all sectors of the economy which are only consistently available for high-income countries. Using comparable data to investigate the effect of financial development on the overall growth-volatility profile in low-income economies could provide important insights into the economic costs of financial underdevelopment.

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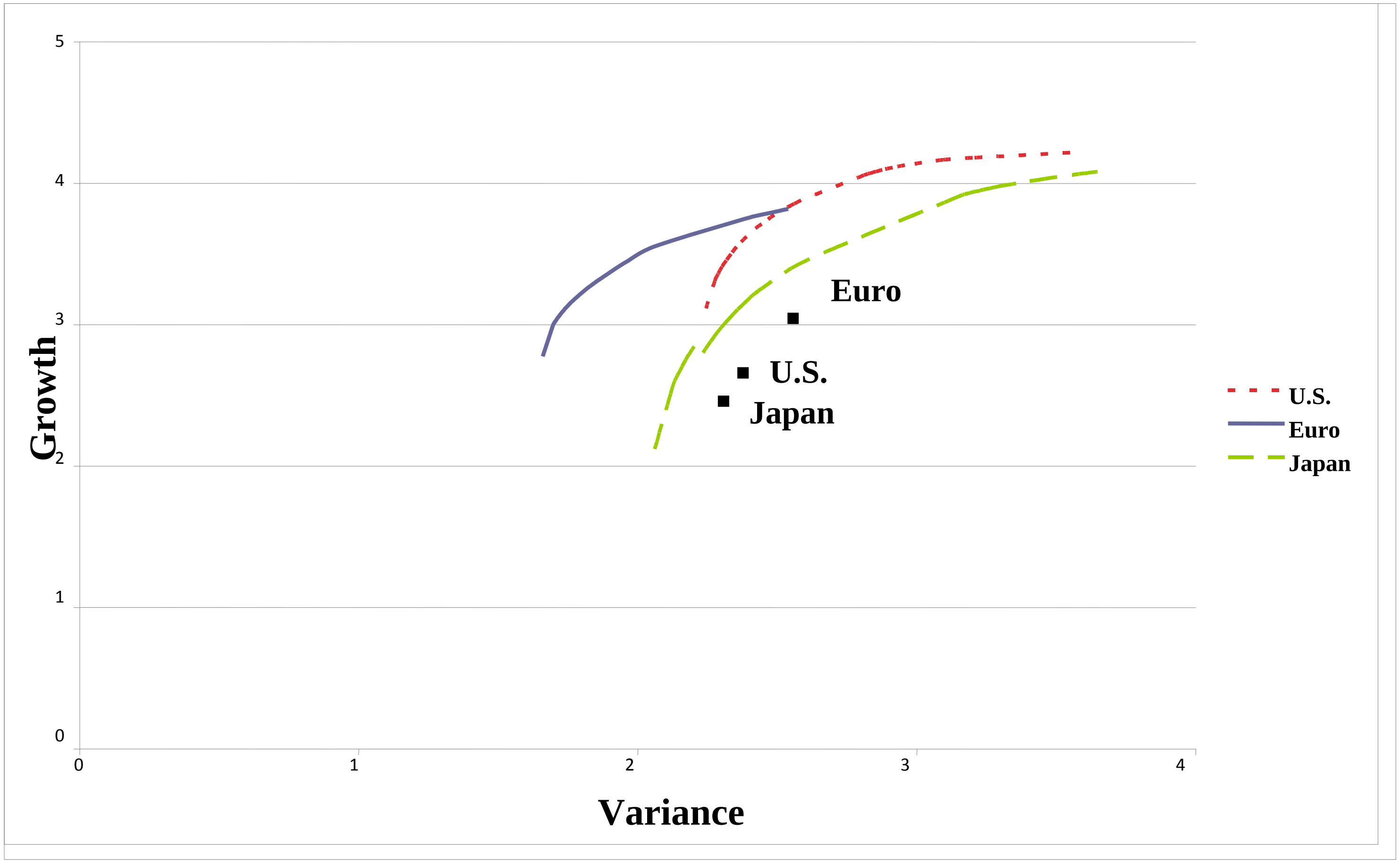
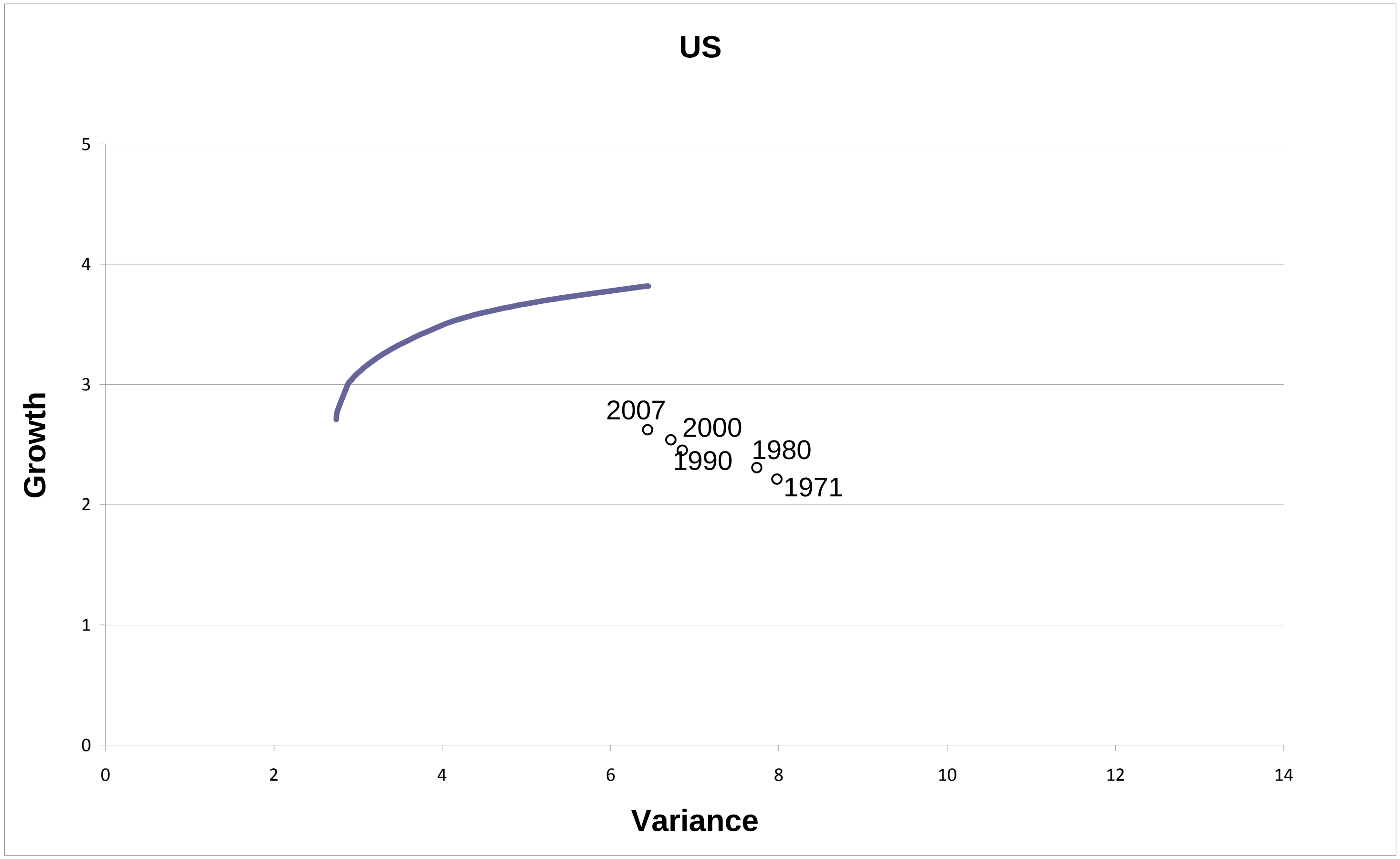
Figure 1. Benchmark vs. actual industrial composition



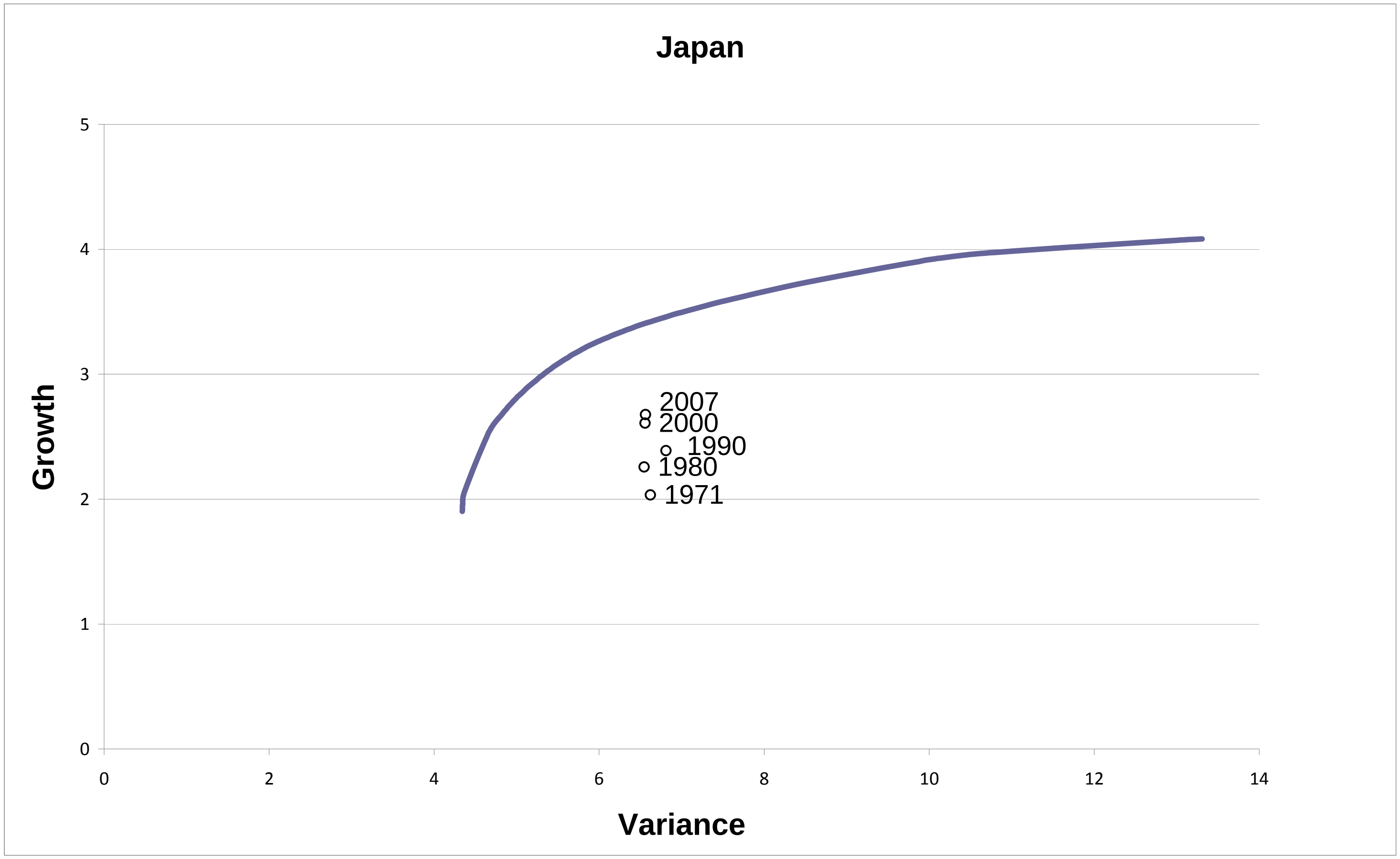
Note: The graph shows the benchmark allocation of industrial output across sectors, based on mean-variance efficiency and calculated using the countries' sectors' long-term growth, volatility, and correlations over the sample period, and the average actual realization of industrial output over the sample period.

Figure 2. Benchmark vs. actual industrial composition over time, U.S.



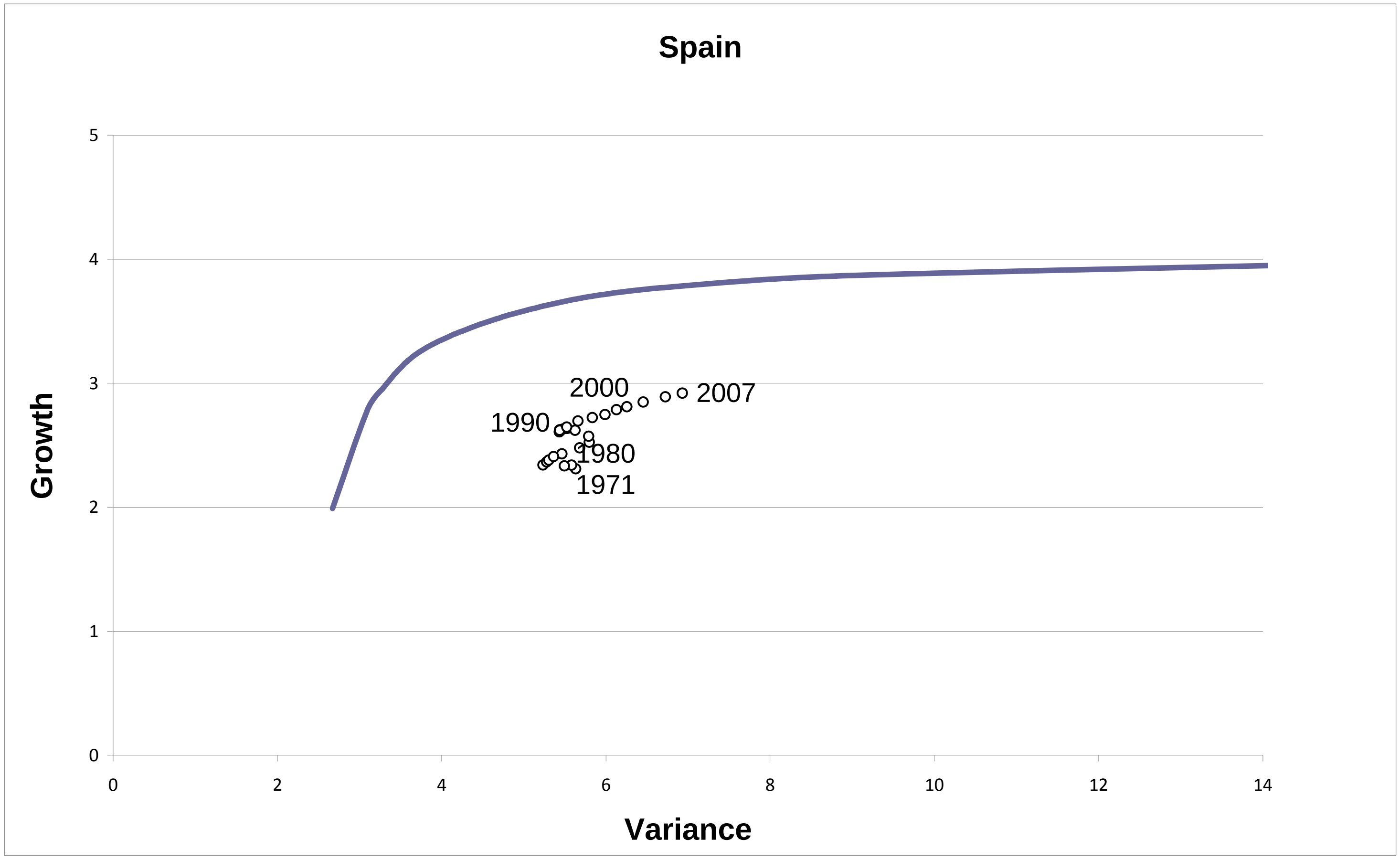
Note: The graph shows the benchmark allocation of industrial output across sectors, based on mean-variance efficiency and calculated using the countries' sectors' long-term growth, volatility, and correlations over the sample period, and the actual realization of industrial output over the sample period over time, for the U.S.

Figure 3. Benchmark vs. actual industrial composition over time, Japan



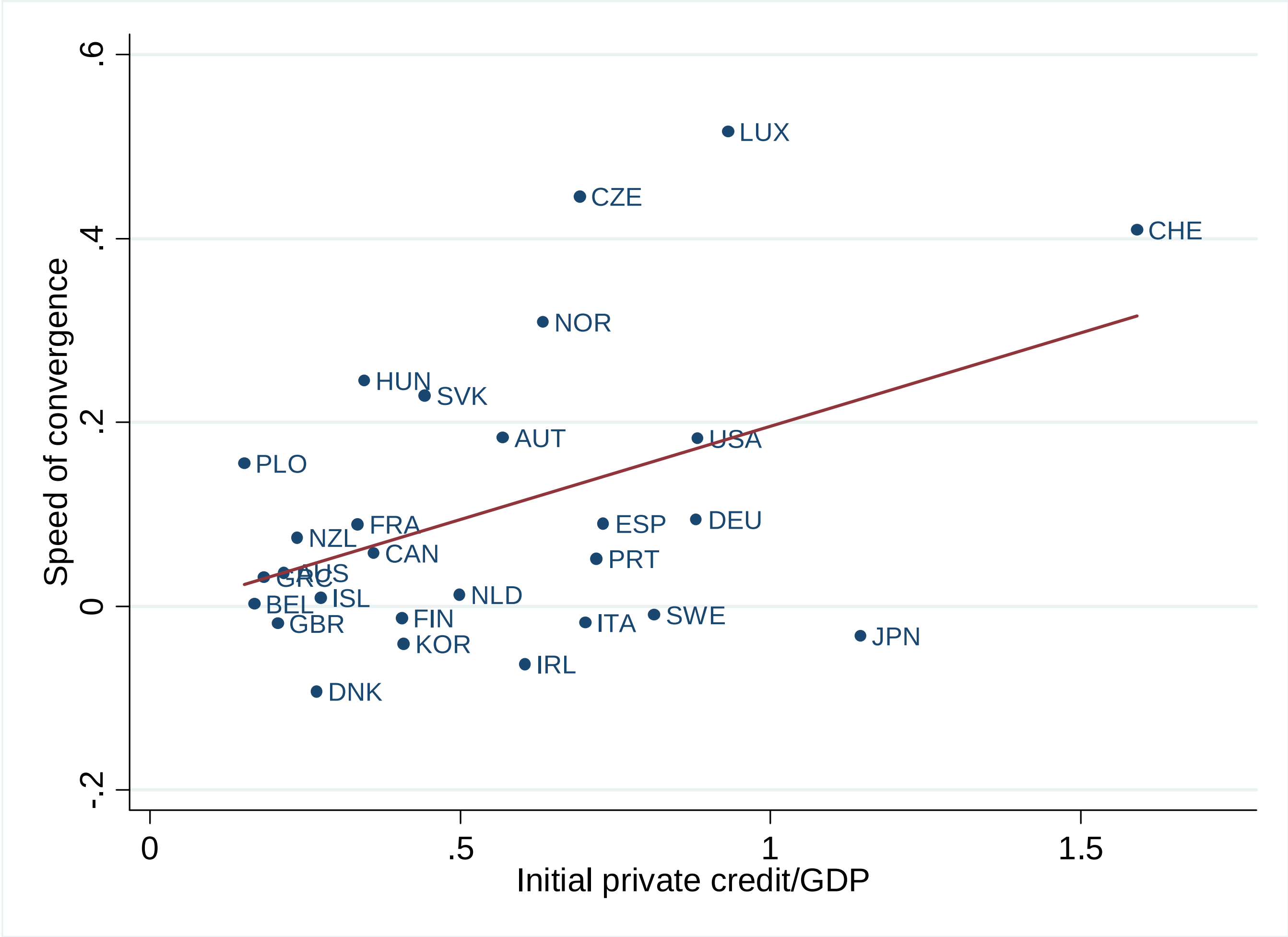
Note: The graph shows the benchmark allocation of industrial output across sectors, based on mean-variance efficiency and calculated using the countries' sectors' long-term growth, volatility, and correlations over the sample period, and the actual realization of industrial output over the sample period over time, for Japan.

Figure 4. Benchmark vs. actual industrial composition over time, Spain



Note: The graph shows the benchmark allocation of industrial output across sectors, based on mean-variance efficiency and calculated using the countries' sectors' long-term growth, volatility, and correlations over the sample period, and the actual realization of industrial output over the sample period over time, for Spain.

Figure 5. Speed of convergence to benchmark industrial composition and initial private credit/GDP



Note: The graph shows each individual country's autoregressive annual speed of convergence over the sample period to the benchmark allocation of output across industrial sectors against beginning-of-sample period private credit to GDP.

Table 1
Value added growth, volatility, and distance to benchmark industrial allocation of output

Country	Average growth	Average volatility	Initial distance	Final distance	Data start	Initial distance	Final distance	Data start
			SIC 1-digit industries			OECD 2-digit industries		
Australia	0.032	0.036	0.332	0.292	1970	0.403	0.304	1970
Austria	0.021	0.018	0.306	0.266	1976	0.354	0.321	1976
Belgium	0.022	0.026	0.541	0.427	1970	0.407	0.347	1970
Canada	0.030	0.035	0.388	0.350	1972	0.341	0.275	1970
Czech Republic	0.020	0.039	0.628	0.617	1993	0.366	0.370	1993
Denmark	0.018	0.024	0.384	0.360	1970	0.350	0.298	1970
Finland	0.029	0.052	0.550	0.533	1970	0.463	0.327	1970
France	0.023	0.025	0.455	0.374	1970	0.298	0.258	1970
Germany	0.006	0.013	0.423	0.377	1991	0.382	0.353	1991
Greece	0.026	0.051	0.467	0.444	1970	0.312	0.272	1970
Hungary	0.004	0.056	0.430	0.415	1991	0.355	0.319	1991
Iceland	0.028	0.087	0.312	0.397	1973	0.417	0.469	1973
Ireland	0.065	0.039	0.620	0.557	1986	0.521	0.379	1986
Italy	0.027	0.037	0.438	0.332	1970	0.376	0.300	1970
Japan	0.023	0.024	0.421	0.422	1970	0.374	0.324	1970
Korea	0.077	0.068	0.588	0.565	1970	0.599	0.425	1970
Luxembourg	0.054	0.035	0.471	0.522	1985	0.357	0.380	1985
Netherlands	0.023	0.025	0.438	0.392	1970	0.400	0.367	1970
New Zealand	0.032	0.036	0.533	0.514	1971	0.318	0.262	1971
Norway	0.034	0.045	0.575	0.709	1970	0.472	0.546	1970
Poland	0.029	0.032	0.422	0.386	1994	0.524	0.503	1994
Portugal	0.022	0.034	0.367	0.363	1977	0.342	0.347	1977
Slovakia	0.023	0.042	0.278	0.277	1993	0.348	0.361	1993
Spain	0.026	0.025	0.320	0.373	1980	0.402	0.373	1980
Sweden	0.021	0.036	0.609	0.503	1971	0.564	0.471	1970
Switzerland	0.006	0.017	0.485	0.467	1990	0.437	0.431	1990
UK	0.007	0.012	0.382	0.276	1986	0.441	0.352	1970
US	0.024	0.026	0.499	0.477	1970	0.349	0.342	1970

Note: The table describes the STAN database for structural analysis. The underlying industry data are at the SIC 1-digit level and OECD 2-digit level (See Appendix B for details). Column (1) lists the average country-level value added growth rate over the period that the country is observed, which is a simple average of the sectoral level growth rates. Column (2) lists long-term standard deviations of growth for each country, again averages across sectors. Columns (3)-(4) and (6)-(7) list our estimates of initial and final distance to the benchmark industrial composition for each country, in a mean-variance efficiency metric, for SIC 1-digit and OECD 2-digit data, respectively. Columns (5) and (8) give the initial year for which data become available for each country. All data are available until 2007.

Table 2
Credit markets: Volumes and liberalization events

Country	**Credit markets**	
	Private credit / GDP	**Liberalization date**
Australia	0.513	1994
Austria	0.841	<1970
Belgium	0.433	<1970
Canada	0.783	<1970
Czech Republic	0.507	1994
Denmark	0.501	1994
Finland	0.571	<1970
France	0.713	<1970
Germany	1.077	<1970
Greece	0.371	1987
Hungary	0.299	1994
Iceland	0.541	<1970
Ireland	0.821	<1970
Italy	0.618	<1970
Japan	1.452	1985
Korea	0.827	1998
Luxembourg	1.054	<1970
Netherlands	1.069	<1970
New Zealand	0.558	1987
Norway	0.869	1985
Poland	0.236	1994
Portugal	0.856	1986
Slovakia	0.504	1994
Spain	0.811	<1970
Sweden	0.956	1985
Switzerland	1.601	<1970
UK	0.653	<1970
US	1.306	1985

Note: The table describes our main financial variable used in the text, private credit over GDP. Column (1) lists the country-level ratio of private credit by all financial institutions, excluding central banks, to GDP, averaged over the sample period. Column (2) lists the year in which the respective country liberalized its banking sector; ‘<1970’ means that those countries’ credit markets are open throughout the period. Data on private credit come from Beck et al. (2010). Data on banking sector liberalization events come from Bekaert et al. (2005).

Table 3
Finance and convergence to benchmark industrial composition: OLS estimation

	Panel A. Country distance to frontier			
	SIC 1-digit data		OECD 2-digit data	
	Full sample	Clean frontier	Full sample	Clean frontier
$D_{c,t-1}\cdot$Credit	-0.0564	-0.1172	-0.0661	-0.0980
	(0.0274)**	(0.0506)**	(0.0271)**	(0.0610)*
$D_{c,t-1}$	0.9045	0.9467	0.9416	0.9438
	(0.0333)***	(0.0552)***	(0.0279)***	(0.0547)***
Credit	0.0211	0.0415	0.0225	0.0347
	(0.0123)*	(0.0231)*	(0.0106)**	(0.0239)
Observations	731	424	678	415

	Panel B. Country-industry distance to frontier			
	SIC 1-digit data		OECD 2-digit data	
	Full sample	Clean frontier	Full sample	Clean frontier
$D_{c,s,t-1}\cdot$Credit	-0.0220	-0.0411	-0.0290	-0.0283
	(0.0068)***	(0.0122)***	(0.0036)***	(0.0059)***
$D_{c,s,t-1}$	0.8806	0.8820	0.9201	0.8894
	(0.0084)***	(0.0134)***	(0.0045)***	(0.0068)***
Credit	0.0024	0.0049	0.0013	0.0010
	(0.0012)**	(0.0023)**	(0.0004)***	(0.0007)
Observations	6,579	3,816	13,560	8,300

Note: The Table reports estimates from fixed effects regressions where the dependent variable is $D_{c,t}$ (Panel A) and $D_{c,s,t}$ (Panel B), both calculated according to equation (5). The regressions are carried out on the sample of all countries for which the number of years with non-missing data is at least as large as the number of industries (Columns labeled "Full sample"), and on the sample of all countries for which the number of years with non-missing data is at least as large as the number of industries and which liberalized their credit markets during the sample period (Columns labeled "Clean frontier"). 'Credit' is the ratio of private credit to GDP. All estimates are from OLS regressions. Country and year fixed effects (Panel A) and country fixed effects interactions with industry fixed effects, as well as year fixed effects (Panel B) included in all regressions. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 4
Finance and convergence to benchmark industrial composition: GMM estimation

	Panel A. Country distance to frontier			
	SIC 1-digit data		OECD 2-digit data	
	Full sample	Clean frontier	Full sample	Clean frontier
$D_{c,t-1} \cdot$ Credit	-0.0911	-0.1443	-0.0919	-0.0984
	(0.0290)***	(0.0495)***	(0.0302)***	(0.0620)*
$D_{c,t-1}$	0.9025	0.9515	0.9540	0.9306
	(0.0320)***	(0.0518)***	(0.0283)***	(0.0547)***
Credit	0.0347	0.0566	0.0262	0.0287
	(0.0132)***	(0.0226)**	(0.0117)**	(0.0245)
Observations	697	402	650	395

	Panel B. Country-industry distance to frontier			
	SIC 1-digit data		OECD 2-digit data	
	Full sample	Clean frontier	Full sample	Clean frontier
$D_{c,s,t-1} \cdot$ Credit	-0.2005	-0.2091	-0.1750	-0.1460
	(0.0139)***	(0.0243)***	(0.0077)***	(0.0128)***
$D_{c,s,t-1}$	0.8225	0.8661	0.8536	0.8052
	(0.0152)***	(0.0246)***	(0.0085)***	(0.0130)***
Credit	0.0230	0.0232	0.0105	0.0067
	(0.0025)***	(0.0044)***	(0.0009)***	(0.0016)***
Observations	6,273	3,618	13,000	7,900

Note: The Table reports estimates from fixed effects regressions where the dependent variable is $D_{c,t}$ (Panel A) and $D_{c,s,t}$ (Panel B), both calculated according to Equation (5). The regressions are carried out on the sample of all countries for which the number of years with non-missing data is at least as large as the number of industries (Columns labeled "Full sample"), and on the sample of all countries for which the number of years with non-missing data is at least as large as the number of industries and which liberalized their credit markets before the sample period (Columns labeled "Clean frontier"). 'Credit' is the ratio of private credit to GDP. All estimates are from a GMM procedure which implements the Arrelano-Bond estimator to account for the presence of a lagged dependent variable in a dynamic panel model. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5
Finance and convergence to benchmark industrial composition: Which sectors converge faster?

	Benchmark = US industry Sharpe ratio	Benchmark = US industry share young firms	Benchmark = US industry Sharpe ratio	Benchmark = US industry share young firms
	SIC 1-digit industries		OECD 2-digit industries	
$D_{c,s,t-1}$ · Credit·Benchmark	-0.0181	-0.2001	-0.0140	-0.2208
	(0.0053)***	(0.0654)***	(0.0014)***	(0.0299)***
$D_{c,s,t-1}$	0.8794	0.8799	0.9231	0.9194
	(0.0086)***	(0.0092)***	(0.0045)***	(0.0048)***
Credit	0.0014	0.0024	0.0011	0.0011
	(0.0011)	(0.0013)*	(0.0004)***	(0.0004)**
Benchmark	0.0071	0.0110	0.0037	0.0122
	(0.0022)***	(0.0061)*	(0.0007)***	(0.0067)*
Observations	6,273	6,273	12,880	12,880

Note: The dependent variable in all cases is $D_{c,s,t}$ calculated according to Equation (5). 'Credit' is the ratio of private credit to GDP. 'US industry Sharpe ratio' is the ratio of long-term growth divided by long-term standard deviation of growth for US industries at the SIC 1-digit (Columns (1) and (2)) or OECD 2-digit (Columns (3) and (4)) level. 'Share of young firms' is the share of firms younger than 2 years out of the full population of firms for US industries at the SIC 1-digit (Columns (1) and (2)) or OECD 2-digit (Columns (3) and (4)) level. Both industry benchmarks are instrumented in all regressions by the predicted sample Sharpe ratio/share of young firms in a regression on country and industry dummies, interacted with the respective US measure of financial development. The US is excluded from all regressions. Country fixed effects interactions with industry fixed effects, as well as year fixed effects, are included in all regressions. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6
Endogeneity of finance

	Credit = Bank liberalization date	Financial sector excluded	Credit = Bank liberalization date	Financial sector excluded
	SIC 1-digit industries		OECD 2-digit industries	
$D_{c,s,t-1} \cdot$ Credit	-0.0330	-0.0141	-0.03714	-0.0292
	(0.0053)***	(0.0050)***	(0.0030)***	(0.0036)***
$D_{c,s,t-1}$	0.8902	0.8669	0.9178	0.9188
	(0.0069)***	(0.0076)***	(0.0039)***	(0.0046)***
Credit	0.0034	0.0019	0.0015	0.0014
	(0.0009)***	(0.0009)***	(0.0003)***	(0.0004)***
Observations	6,930	5,848	14,140	12,882

Note: The dependent variable in all cases is $D_{c,s,t}$ calculated according to Equation (5). 'Credit' is the ratio of private credit to GDP. 'Bank liberalization date' equals 1 for the years after the country liberalized its domestic credit market, and 0 otheriwise. Data on those come from Bekaert et al. (2005). Financial sector (SIC industry #8, OECD industry #65-67) is excluded from the regressions in Colums (2) and (4). Country fixed effects interactions with industry fixed effects, as well as year fixed effects, are included in all regressions. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7
Optimal vs. "naive" diversification

	Panel A. Country SIC 1-digit data			
	Corr=0	Ogive index	HHI	Gini coefficient
$D_{c,t-1} \cdot \text{Credit}$	-0.0317	0.0224	0.0159	0.0020
	(0.0243)	(0.0192)	(0.0194)	(0.0182)
Observations	731	731	731	731

	Panel B. Country OECD 2-digit data			
	Corr=0	Ogive index	HHI	Gini coefficient
$D_{c,t-1} \cdot \text{Credit}$	-0.0649	-0.0229	-0.0325	-0.0421
	(0.0398)	(0.0179)	(0.0232)	(0.0263)
Observations	678	678	678	678

Note: The dependent variable is $D_{c,t}$ in Column (1), calculated by setting correlations equal to 0 in Equation (5); the Ogive index in Column (2); the Herfindhal-Hirshmann index in Column (3); and the Gini coefficient in Column (4); See Section IV.C for details on how those are calculated. 'Credit' is the ratio of private credit to GDP. Country fixed effects and year fixed effects are included in all regressions. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8
Alternative measures of finance

			Panel A. SIC 1-digit data			
$D_{c,s,t-1}\cdot$ Credit			-0.0221 (0.0078)***	-0.0185 (0.0078)***	-0.0366 (0.0154)**	-0.0141 (0.0032)***
$D_{c,s,t-1}\cdot$ Stock	-0.0002 (0.0056)					
$D_{c,s,t-1}\cdot$ Bonds		-0.0029 (0.0080)				
$D_{c,s,t-1}\cdot$ Trade			-0.0001 (0.0001)			
$D_{c,s,t-1}\cdot$ Gross foreign assets				-0.0011 (0.0009)		
$D_{c,s,t-1}\cdot$ Net foreign assets				0.0204 (0.0085)**		
Observations	6,669	6,498	6,480	6,399	3,063	3,516
			Panel B. OECD 2-digit data			
$D_{c,s,t-1}\cdot$ Credit			-0.0149 (0.0043)***	-0.0248 (0.0042)***	-0.0311 (0.0057)***	-0.0195 (0.0034)***
$D_{c,s,t-1}\cdot$ Stock	-0.0126 (0.0034)***					
$D_{c,s,t-1}\cdot$ Bonds		-0.0066 (0.0040)*				
$D_{c,s,t-1}\cdot$ Trade			-0.0005 (0.0001)***			
$D_{c,s,t-1}\cdot$ Gross foreign assets				-0.0171 (0.0053)***		
$D_{c,s,t-1}\cdot$ Net foreign assets				-0.0022 (0.0007)***		
Observations	13,760	13,380	13,560	13,380	7,427	6,133

Note: The dependent variable is $D_{c,s,t}$, calculated according to Equation (5). 'Stock' is the ratio of stock market capitalization to GDP. 'Bonds' is the ratio of private plus public bonds to GDP. 'Trade' is the ratio of exports plus imports to GDP. 'Gross foreign assets' is the ratio of foreign assets plus liabilities to GDP. 'Net foreign assets' is the ratio of foreign assets to GDP. In column (5), the analysis is performed on the countries which fall in the bottom half of the distribution of financial sector share of total value added in the intial year of data availability. In column (6), the analysis is performed on the countries which fall in the top half of the distribution of financial sector share of total value added in the intial year of data. Country fixed effects interactions with industry fixed effects, as well as year fixed effects, are included in all regressions. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 9
Finance, law, and regulation

	Panel A. Country distance to frontier			
	SIC 1-digit data		OECD 2-digit data	
	Full sample	Clean frontier	Full sample	Clean frontier
$D_{c,t-1}\cdot$ Credit	-0.0607	-0.0613	-0.0387	-0.0603
	(0.0304)**	(0.0317)**	(0.0143)***	(0.0283)***
$D_{c,t-1}\cdot$ Entry time	0.0016	0.0020	0.0018	0.0007
	(0.0025)	(0.0026)	(0.0011)*	(0.0017)
$D_{c,t-1}\cdot$ Investor protection	-0.0176	-0.0202	0.0114	0.0114
	(0.0246)	(0.0260)	(0.0086)	(0.0102)
$D_{c,t-1}\cdot$ Contract enforcement	0.0003	0.0003	0.0001	0.0001
	(0.0001)***	(0.0001)***	(0.0001)	(0.0001)
$D_{c,t-1}$	0.8818	0.8998	0.9428	0.9676
	(0.1803)***	(0.1903)***	(0.0564)***	(0.0783)***
Observations	680	619	577	346

	Panel B. Country-industry distance to frontier			
	SIC 1-digit data		OECD 2-digit data	
	Full sample	Clean frontier	Full sample	Clean frontier
$D_{c,s,t-1}\cdot$ Credit	-0.0184	-0.0337	-0.0273	-0.0230
	(0.0074)**	(0.0128)***	(0.0042)***	(0.0073)***
$D_{c,s,t-1}\cdot$ Entry time	0.0020	0.0024	0.0020	0.0018
	(0.0009)**	(0.0016)	(0.0004)***	(0.0009)***
$D_{c,s,t-1}\cdot$ Investor protection	-0.0210	-0.0211	-0.0387	-0.0377
	(0.0082)***	(0.0123)*	(0.0045)***	(0.0066)***
$D_{c,s,t-1}\cdot$ Contract enforcement	0.0001	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)***	(0.0001)*	(0.0001)***
$D_{c,s,t-1}$	0.9610	0.9273	1.1162	1.0623
	(0.0502)***	(0.0897)***	(0.0306)***	(0.0474)***
Observations	6,120	3,645	12,240	7,620

Note: The dependent variable is $D_{c,t}$ (Panel A) and $D_{c,s,t}$ (Panel B), both calculated according to Equation (5). 'Entry time' is the number of days necessary to start a business in the respective country. 'Investor protection' is an average of three indices of degree of protecting private investors. 'Contract enforcement' is the number of days necessary to settle a contractual dispute in court. Columns (1) and (3) report the regression estimates from the full unbalanced panel covering the period 1970-2006; Columns (2) and (4) report the regression estimates after excluding countries which liberalized their credit markets during the sample period. Country and year fixed effects are included in all regressions (Panel A). Country fixed effects interactions with industry fixed effects, as well as year fixed effects, are included in all regressions (Panel B). White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 10
Finance and stages of diversification

	Panel A. Country SIC 1-digit data			
	Low initial diversification		High initial diversification	
$D_{c,t-1} \cdot$ Credit	-0.0831 (0.0178)***		-0.0331 (0.0482)	
$D_{c,t-1} \cdot$ Stock		-0.0231 (0.0130)*		0.0927 (0.0612)
Observations	351	355	380	386
	Panel B. Country OECD 2-digit data			
	Low initial diversification		High initial diversification	
$D_{c,t-1} \cdot$ Credit	-0.0464 (0.0169)***		-0.0997 (0.0599)*	
$D_{c,t-1} \cdot$ Stock		-0.0348 (0.0200)*		0.0235 (0.0476)
Observations	307	313	371	375

Note: The dependent variables is $D_{c,t}$, calculated according to equation (5). 'Credit' is the ratio of private credit to GDP. 'Stock' is the ratio of stock market capitalization to GDP. 'Low initial diversification' refers to the countries which are in the bottom half of the allocative-efficiency implied diversification distribution in the first year of data availability. 'High initial diversification' refers to the countries which are in the top half of the allocative-efficiency implied diversification distribution in the first year of data availability. Country fixed effects and year fixed effects are included in all regressions. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 11
Finance and convergence to benchmark industrial composition in larger economic zones

	OLS	Arellano - Bond	Benchmark= US industry Sharpe ratio	Benchmark= US industry share young firms	Financial sector excluded	2SLS
			SIC 1-digit data			
$D_{c,s,t-1}$ · Credit	-0.1147	-0.1729			-0.0966	-0.1619
	(0.0239)***	(0.0247)***			(0.0239)***	(0.0359)***
$D_{c,s,t-1}$ · Credit			-0.0966	-0.7495		
· Benchmark			(0.0230)***	(0.1816)***		
$D_{c,s,t-1}$	0.9121	0.8694	0.8899	0.9214	0.9021	0.8989
	(0.0228)***	(0.0219)***	(0.0257)***	(0.0229)***	(0.0308)***	(0.0243)***
Benchmark			0.0390	-0.0009		
			(0.0086)***	(0.0005)*		
Observations	135	126	135	135	120	135

Note: The dependent variable is $D_{c,s,t}$, calculated according to Equation (5), using aggregated data for the 12 original euro zone countries. 'Credit' is the ratio of private credit to GDP for the 12 original euro zone countries. Column (1) reports the OLS regression estimates from the full unbalanced panel covering the period 1991-2007. Column (2) reports the estimates from a GMM procedure which implements the Arrelano-Bond estimator to account for the presence of a lagged dependent variable in a dynamic panel model. 'US industry Sharpe ratio' is the ratio of long-term growth divided by long-term standard deviation of growth for US industries at the SIC 1-digit level. 'Share of young firms' is the share of firms younger than 2 years out of the full population of firms for US industries at the SIC 1-digit level. Financial sector (SIC industry #8) is excluded from the regression in Column (5). In Column (6), the credit variable has been instrumented using an indicator variable equal to 1 after 1999 (the year of the introduction of the euro). Industry and year fixed effects included in all regressions. White (1980) standard errors appear below each coefficient in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix A. Variables and sources

Value added	Country-industry estimate of real annual growth of value added. Available until 2007 for 9 SIC 1-digit and 20 OECD 2-digit industries for 28 OECD countries, at best staring in 1970. Constructed by deflating nominal growth rates. Source: STAN Database for Structural Analysis.
Share young firms	Share of firms younger than 2 years out of the total population of firms, for US corporations. Calculated for 1-digit SIC industries. Average for the years 1985-95. Source: Dun & Bradstreet.
Credit	The value of total credits by financial intermediaries to the private sector in each country, available with annual frequency. Excludes credit by central banks. Calculated using the following deflation method: {(0.5)*[Ft/P_et + Ft-1/P_et-1]}/[GDP_t/P_at] where F is credit to the private sector, P_e is end-of period CPI, and P_a is average annual CPI. Source: Beck et al. (2010).
Stock	Value of listed shares to GDP, calculated using the following deflation method: {(0.5)*[Ft/P_et + Ft-1/P_et-1]}/[GDPt/P_at] where F is stock market capitalization, P_e is end-of period CPI, and P_a is average annual CPI. Source: Beck et al. (2010).
Bonds	Private domestic debt securities issued by financial institutions and corporations plus public domestic debt securities issued by government as a share of GDP, calculated using the following deflation method: {(0.5)*[Ft/P_et + Ft-1/P_et-1]}/[GDPt/P_at] where F is amount outstanding of private plus public domestic debt securities, P_e is end-of period CPI, and P_a is average annual CPI. Source: Beck et al. (2010).
Trade	The sum of exports and imports of the total economy over GDP. Available until 2007 for 9 SIC 1-digit and 20 OECD 2-digit industries for 28 OECD countries, at best staring in 1970, with annual frequency. Source: STAN Database for Structural Analysis.
Gross foreign assets	The sum of total foreign assets and liabilities over GDP, with annual frequency. Source: Lane and Milesi-Ferretti (2007).
Net foreign assets	Total foreign assets over GDP, with annual frequency. Source: Lane and Milesi-Ferretti (2007).
Bank liberalization	Dummy variable equal to 1 after the year in which domestic credit markets were open to foreign participation. Source: Bekaert et al. (2005).
Entry time	The time (in days) it takes to register a new business entity in the respective country. Data aggregated over the time period. Source: Doing Business Database.
Investor protection	Average of three indices of protection of investors: trasparency of transactions, liability for self-dealing, and shareholders' ability to sue officers and directors for misconduct. Data aggregated over the time period. Source: Doing Business Database.
Contract enforcement	The time (in days) it takes to resolve a contractual dispute in the respective country. Data aggregated over the time period. Source: Doing Business Database

Appendix B. Sectoral coverage

1. SIC 1-digit Classification (9 sectors)

1. Agriculture, Hunting, Forestry, and Fishing
2. Mining and Quarrying
3. Manufacturing
4. Electricity, gas, and water supply
5. Construction
6. Wholesale and retail trade - restaurants and hotels
7. Transport, storage and communications
8. Finance, insurance, real estate, and business services
9. Community, social, and personal services.

2. OECD 2-digit Classification (20 sectors)

01-05. Agriculture, Hunting, Forestry, and Fishing
10-14. Mining and Quarrying
15-16. Food Products, Beverages, and Tobacco
17-19. Textiles, Textile Products, Leather, and Footwear
20. Wood and Products of Wood and Cork
21-22. Pulp, Paper, Paper Products, Printing, and Publishing
23-25. Chemical, Rubber, Plastics, and Fuel Products
26. Other Non-Metallic Mineral Products
27-28. Basic Metals and Fabricated Metal Products
29-33. Machinery and Equipment
34-35. Transport Equipment
36-37. Manufacturing Not Elsewhere Specified and Recycling
40-41. Electricity, Gas, and Water Supply
45. Construction
50-52. Wholesale and Retail Trade
55. Hotels and Restaurants
60-64. Transport, Storage and Communications
65-67. Financial Intermediation
70-74. Real Estate, Renting, and Business Activities
75-99. Community, Social, and Personal Services