INSTITUTE
OF ECONOMIC STUDIES
Faculty of Social Sciences
Charles University

CONSISTENCY OF BANKS' INTERNAL PROBABILITY OF DEFAULT ESTIMATES

Barbora Stepankova

IES Working Paper 44/2020

Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Bibliographic information:
Stepankova, B. (2020): "Consistency of Banks' Internal Probability of Default Estimates" IES Working Papers 44/2020. IES FSV. Charles University.

This paper can be downloaded at: http://ies.fsv.cuni.cz

Consistency of Banks' Internal Probability of Default Estimates

Barbora Stepankova[a]

[a]Institute of Economic Studies, Faculty of Social Sciences, Charles University
Opletalova 26, 110 00, Prague, Czech Republic
Email: barbora.stepankova@hotmail.com

November 2020

Abstract:
Some financial institutions can use internally developed credit risk models to determine their capital requirements. At the same time, the regulatory framework governing such models allows institutions to implement diverse rating systems with no specified penalty for poor model performance. To what extent the resulting model risk { potential for equivalent models to deliver inconsistent outcomes { is prevalent in the economy is largely unknown. We use a unique dataset of 4.9 million probability of default estimates provided by 28 global IRB banks, covering the January 2016 to June 2020 period, to assess the degree of variance in credit risk estimates provided by multiple banks for a single entity. In line with the prior literature, we find that there is a substantial variance in outcomes and that it decreases with the amount of available information about the assessed entity. However, we further show that the level of variance is highly dependent on the entity type, its industry and locations of the entity and contributing banks; banks report a higher deviation from the mean credit risk for foreign entities. Further, we conclude that a considerable part of the variance is systematic, especially for fund models. Finally, utilising the latest available data, we show the massive impact of the COVID-19 pandemic on dispersion of credit estimates.

JEL: C12, G21, G32
Keywords: Banking, Credit Risk, Bank Regulation

Acknowledgements: This work was supported by the Charles University PRIMUS program (project PRIMUS/19/HUM/17).

1 Introduction

Credit risk, i.e. the loss resulting from a counterparty failing to meet its obligations in accordance with agreed terms, is a key consideration in banking and the financial industry more broadly. The recent trends in regulation and supervision of the financial industry resulted in greater independence of financial institutions in managing their risks. The Basel II Accord was a significant milestone in this regard: it allows banks to use internal models to determine their capital requirements through estimation of the entity's probability of default (PD), the loss given default (LGD) and the exposure at default (EAD). Although such models are regulated, banks are allowed to implement diverse rating systems and there is no specified penalty for poor model performance. Instead, the regulatory framework works with an implicit assumption that banks produce accurate risk estimates given the information available to them, despite the fact that banks may be motivated to exploit their discretion and optimise the reported inputs to the models (Plosser and Santos, 2014).

This raises a question about comparability of outputs captured by model risk, which can be literally defined as the potential for different models to provide inconsistent outcomes (Danielsson et al., 2016). Several studies have investigated the consistency of banks' internal model outputs and factors that may affect it (e.g. Berg and Koziol, 2017, Firestone and Rezende, 2016 and Plosser and Santos, 2014), showing a significant variance in the PD estimates, indicating that more explicit rules for banks' internal credit rating systems may be required. In absence of a tightened regulation, the underlying differences in banks' credit models may result in capital requirements that are no longer comparable across banks, especially if the differences are systematic. However, further evidence is required in this regard as the studies work with a relatively small sample of banks, specific type of credit instruments or they focus on a particular geographical area.

This paper contributes to the existing literature on model risk of credit risk estimates by analysing a unique dataset with a vastly greater number of banks and their entities than in the prior literature, as well as a more comprehensive geographical and industry coverage. We investigate a longitudinal dataset of PD estimates from 28 global banks that use the internal rating based (IRB) approach to estimate their regulatory capital. The data cover monthly assessments on more than 60,000 entities including corporates, financials, funds and governments, and multiple regions for the January 2016 to June 2020 period, accounting in total for 4.88 million month-entity-bank observations. In addition, we further extend the analysis from the prior literature in three ways. First, we study new factors affecting the variance in credit risk estimates, including location of entities and banks, entity type, industry classification or existence of rating by a rating agency. Second, we measure the magnitude of systematic effects in the overall model risk individually for each entity type representing different internal models. Finally, utilising the latest available data, we show the impact of the COVID-19 pandemic on credit risk estimates and their variance.

The next section provides a brief overview of banks' credit rating models and the relevant literature, Section 3 presents the dataset and its descriptive statistics and describes the empirical strategy, Section 5 discusses the analytical results and Section 6 concludes the work.

2 Banks' internal credit rating models

Credit risk models developed internally by banks are a result of the need to quantify the amount of economic and regulatory capital required to support banks' risk taking activities (Chatterjee et al., 2015). Indeed, for many financial institutions, credit risk is a major component of the overall risk to the institution and, if inappropriately managed, may have substantial secondary effects on the financial sector as a whole. Hence, it is closely monitored by regulators. The Basel II Accord, introduced in 2004, served as a basis for national rule-making and implementation processes, allowing institutions to use their own internal credit risk models but requiring them to align their models with the regulatory requirements, such as portfolio invariance, separation of corporate, sovereign, bank, retail and equity models, and use of appropriate risk parameters.

This study focuses on banks using the IRB approach for credit risk estimation, i.e. banks which use their own quantitative models to estimate probability of default. Such models must meet various minimum guidelines defined by the accord and banks have to prove that their risk estimation systems provide reasonably accurate and consistent estimates. Credit risk models typically work with a number of well-defined parameters, such as leverage (financial debt, bank debt, interest paid), profitability (value added, profit-loss ratio, EBITDA), liquidity (cash, current liabilities), capital structure (equity, current assets), dimension (turnover, employees), and macroeconomic indicators (aggregate default rate, credit growth, GDP growth). At the same time, the exact model specifications evolve over time and differ by bank, resulting in variance in credit risk estimates for a single entity assessed by multiple banks. To make things worse, many banks have recently started adopting the vast array of often highly disparate and hard-to-follow artificial intelligence algorithms in their credit risk models to consider the large amounts of data available on individuals and organisations, further exacerbating the problem of model heterogeneity.

Indeed, banks' credit risk models are subject to various risks relating to uncertainty at multiple levels of the risk assessment process (Danielsson et al., 2016). These include particularly the validity of model input parameters – their completeness, accuracy and recency – appropriateness of the credit risk model choice and its theoretical foundations. Accuracy of model parameters is discussed e.g. by Boucher et al. (2014), Glasserman and Xu (2014) and Alexander and Sarabia (2012), who distinguish between parameter uncertainty, i.e. the inherent error in estimation of model's parameters, and an inappropriate form of the statistical model to estimate such parameters in the first place. Model appropriateness and validity, discussed e.g. by Danıelsson (2002) and O'Brien and Szerszen (2014), refers principally to the difficulty (or impossibility) to identify the best-performing model due to latency of credit risk as a concept and inability to directly estimate it using observable data. Regardless of the model risk source, its implications can be substantial if it creates systematical differences in credit risk estimates.

Despite the importance of banks' internal credit rating systems for their capital requirements and the broader regulatory purposes, much of the inherent differences in banks' models are still unknown. This is partially because the models are, as an intellectual property, kept secret, without a direct access to most researchers. One way of circumventing this limitation is by looking at the model outputs rather than the models themselves, analysing the variance in PD estimates for a single entity assessed by multiple banks. However, there are only a handful of such studies available. In an earlier work, Firestone and Rezende (2016) use data on syndicated loans from nine US banks, showing that banks' PD estimates substantially differ, but that this variance is mostly random, i.e. that banks generally do not set their estimates systematically above or below the median bank. The variance in PD estimates is confirmed by Jacobson et al. (2006), who use data from two Swedish banks over the 1997-2000 period, as well as Plosser and Santos (2014), who investigate the incentives for banks to bias their internally generated risk estimates through comparison within loan syndicates using

Q1/2010-Q3/2013 quarterly data from 188 banks who participated in the Shared National Credit Program in the US, accounting for almost 80,000 credit-quarters. They concluded that there are significant differences in the borrower's probability of default as estimated by the individual banks, ranging up to 1 pp. The results are also in line with a more recent paper by Berg and Koziol (2017), who utilise quarterly data from 40 banks and 17,000 corporate borrowers available through the German credit registry dataset. Looking specifically at the 2008-2012 period. They show that the difference in banks' capital ratios can vary by up to ± 10%, equivalent to approximately 1 pp, when using the average risk weights from all banks providing a PD estimate for a given entity instead of risk weights based on banks' individual PD estimates. Other studies on the topic include RMA Capital Working Group (2000) or Carey (2002); regulators often focus on small and hypothetical loan portfolios (Financial Services Authority, 2012; Basel Committee on Banking Supervision, 2013).

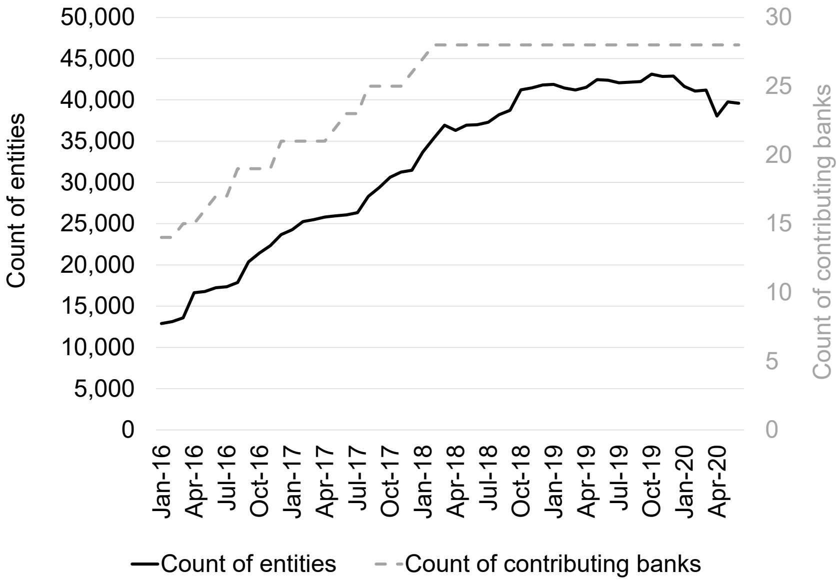
3 Data

The unique empirical dataset used in our study is provided by Credit Benchmark and contains monthly PD estimates from 28 global banks that were approved to use the IRB approach to credit risk modelling. The company pools together banks' internal PD estimates and aggregates them to create entity- and portfolio-level credit risk benchmarks. The banks are clients of Credit Benchmark and the benchmarks allow banks to compare themselves against their peers. On a monthly basis, banks submit their internal hybrid-through-the-cycle (H-TTC) one-year PD estimates together with entity-specific information including name, country of risk and industry classification. PDs do not capture recovery rate and all banks use the same PD concept (credit risk only, time horizon, reporting date), which allows for a direct comparison across banks. Credit Benchmark maps the banks' data to entity reference data from multiple data providers including FactSet, Dun & Bradstreet and Thomson Reuters, and identifies which observations evaluate the risk for the same entity. We have access to the mapped PD estimate contributions by banks as well as the aggregated entity-level outputs including the mean PD. Banks' portfolios are not stable over the time as they drop some exposures and add other entities to their portfolio. Regulators require the risk estimates to be reviewed at least on annual basis to reflect newly available information.

The dataset consists of 24.8 million month-entity-bank observations covering the 01/2016-06/2020 period, with 4.88 million month-entity-bank observations (covering 1.75 million month-entities and 60,220 unique entities) used in the final analysis after the following data cleaning steps. First, observations had to be dropped due to non-existent mapping to the reference data including country and industry classification (24.4%), due to duplicated rows (2.4%) or because they are marked as inactive by the contributing banks (3.0%). Second, as the focus of this study is on dispersion in banks' credit risk estimates at the entity level, we limited the sample to entities with credit risk estimates from at least two banks, excluding 49.9% of observations. Third, we removed defaulted entities, i.e. all entities where at least one bank reported a PD of 100% in a given month, as well as entities emerging from default, as the timing often differs across banks (0.4%). Finally, we dropped corporate entities with PD estimates greater than 3 Bps (0.3%), which is the floor for calculating capital requirements based on internal models under the Basel Accord, as some banks report the values before regulatory overwrite and the inconsistency in methodologies would artificially increase the resulting dispersion.

Banks' portfolios cover entities from all regions and entity type classifications. The dataset includes information on entity's country of risk and industry classification, monthly credit rating estimates from S&P, public/private entity identifier, and, for corporates, size based on sales, number of employees and company family structure. Each of the 28 banks contributed for at least 29 out of the total 54 months and covered at least 1,000 distinct entities with credit estimates from two and more banks. To analyse the impact of bank's location on PD estimates, each bank is assigned a country of domicile based on the location of its headquarters. The banks in our sample are located in United States, South Africa, United Kingdom, continental Europe, Canada and Asia-Pacific. In order to protect the confidential nature of the data, we do not identify the banks in our sample. The number of participating banks increases over time, starting with 14 banks in Jan-16 and reaching the full sample of 28 banks in Feb-18, which impacts the number of entities used in the study as shown in Figure 1. The number of entities continuously increased in 2016-2019 and then started to drop in 2020 as banks adjusted their portfolios at the onset of the COVID-19 crisis . For summary, Table 1 lists all collected variables and Table 2 presents the summary of the data.

Figure 1: Time series of count of entities



The month-entity-bank PD estimates are aggregated to month-entity mean PD using geometric average of the individual PDs to reflect the close to log-normal distribution of the data, illustrated by the large skewness and kurtosis of both observation and entity level PDs (see Table 2).[1] Analogously, we can calculate the entity-level PD dispersion parameter (see Equation 2) and depth, i.e. the number of banks contributing to a single month-entity. The mean PD of entity i at time t across banks $b \in \{1, \ldots, n_{i,t}\}$ is defined as

$$PD_{i,t}^{GMean} = \exp\left(\frac{\sum_{b=1}^{n_{i,t}} lnPD_{i,t,b}}{EDep_{i,t}}\right), \tag{1}$$

where $EDep_{i,t}$ is the number of banks contributing to entity i at time t (i.e. entity's depth). The average PD is 0.57% with the interquartile range of 0.05% to 0.53%.

To calculate dispersion, we follow Berg and Koziol (2017) and use standard deviation of PD

[1]Both geometric and arithmetic approaches to aggregation of PDs are valid are there is no consensus in the existing literature. Credit Benchmark uses arithmetic aggregation.

estimates in logarithms. Consequently, dispersion of banks' PD estimates for entity i at time t across banks $b \in \{1, \ldots, n_{i,t}\}$ is calculated as

$$D_{i,t}(lnPD) = \hat{\sigma}(lnPD_{i,t,b=1}, \ldots, lnPD_{i,t,b=n_{i,t}}) = \sqrt{\frac{\sum_{b=1}^{n_{i,t}}(lnPD_{i,t,b} - lnPD_{i,t}^{GMean})^2}{EDep_{i,t} - 1}}. \qquad (2)$$

Note that dispersion measures the level of disagreement across banks regarding entity's credit and Berg and Koziol (2017) interpret it as a proxy for model risk of the banks' underlying internal rating models. The average dispersion is 0.69 with an interquartile range from 0.35 to 0.94.

Figure 2: Time series of Mean PD and Dispersion

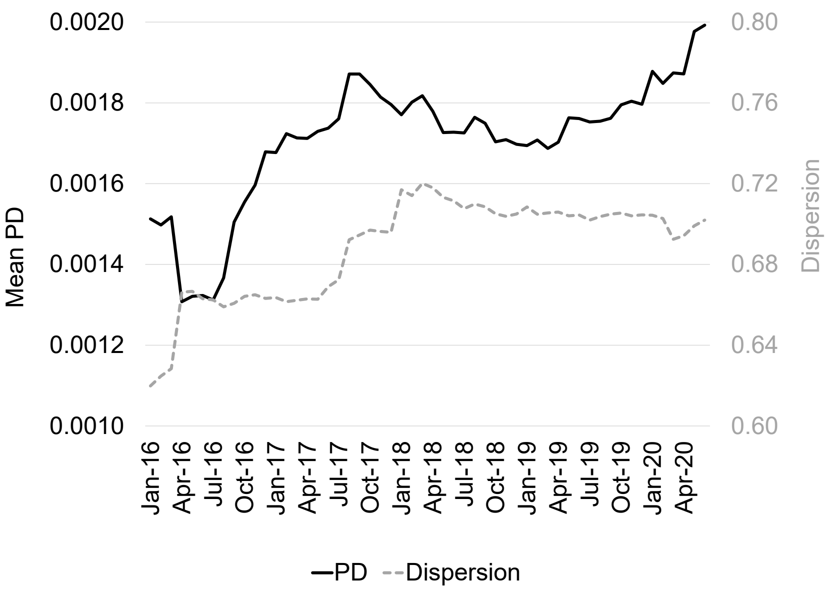


Figure 2 shows the changes in the mean PD and dispersion averaged across all entities. The changes in the measures are driven by both changes in the risk estimates and changes in the set of contributed observations.

4 Methodology

Our study broadly follows the analysis by Berg and Koziol (2017), who focus on dispersion of credit risk estimates provided by 40 German IRB banks. They analyse determinants of across-bank dispersion of PD estimates, their systematic vs idiosyncratic differences, and determinants of the systematic differences. We extend their work by including credit risk estimates of financials, funds and governments, analysing the importance of bank and entity location, adding more details on the underlying entities, such as size, region, industry classification and existence of external ratings, and by including global banks in the analysis. Further, we provide an overview of the impact of COVID-19 on both credit risk levels and disagreement across banks in different regions.

This is done in four steps. First, we analyse the determinants of the dispersion, followed by the role of location and the size of systematic effects. Finally, we provide insights into the impact of COVID-19.

Table 1: Description of variables

The variables are presented in three sections: characteristics of bank observations (Panel A), characteristics of entities (Panel B) and characteristics of contributing banks (Panel C). PDs can be expressed in decimals (0.0050), percentages (0.5%) or basis points (50 Bps).

Variable	Unit	Description
Panel A: bank observation characteristics		
PD estimate	Decimals	Banks-specific view of entity credit risk, measured as hybrid-through-the-cycle probability of default over a one-year horizon, ranging from 0 to 1. $PD_{j,i,t}$ is PD estimate on entity i from bank j at time t.
PD estimate in logs	Log decimals	Natural logarithm of PD estimate, $lnPD_{j,i,t} = log(PD_{j,i,t-1})$.
Panel B: entity characteristics		
Depth	Count	Number of PD observations received from banks per entity, $EDep$.
% Foreign contributors	Percentage	Percentage of banks contributing to the given entity that have headquarters in a different country than the entity's country of risk.
Mean PD	Decimals	Across-bank aggregated measure of entity credit risk, calculated as geometric mean of PD estimates for the given entity, $PD_{i,t}^{GMean} = exp(\frac{\sum_{b=1}^{n} lnPD_{i,t,b}}{N})$.
Mean PD in logs	Log decimals	Natural logarithm of Geometric mean PD, $lnPD_{i,t}^{GMean} = log(PD_{i,t}^{GMean})$.
Dispersion	Log decimals	Across-bank measure of disagreement of banks about credit risk of the entity calculated as standard deviation of PD estimates in logs, $D_{i,t} = \hat{\sigma}(lnPD_{i,t,b=1}, \ldots, lnPD_{i,t,b=n}) = \sqrt{\frac{\sum_{b=1}^{n}(lnPD_{i,t,b} - lnPD_{i,t}^{GMean})^2}{N-1}}$.
Region	Categorical	Entity's region of risk: North America, Europe, Asia, Middle East, etc., $EReg$.
Country	Categorical	Entity's country of risk: United States, United Kingdom, Luxembourg, Canada, Germany, South Africa, etc., $ECoun$.
Entity type	Categorical	Entity type classification: Funds, Corporates, Financials, Governments, $ETyp$.
SP	Numerical rating	Entity' credit rating provided by S&P, represented by notches (AAA=1, AA+=2, ..., C=21).
Public	Categorical	Indicator variable, equal to 1 for public entities and 0 for private entities, as defined by FactSet.
Industry	Categorical	Industry classification: Basic Materials, Consumer Goods, Consumer Services, Health Care, Industrials, Oil and Gas, Technology, Telecommunications and Utilities, $EInd$. Available for corporates only.
Sales	$m	Annual sales available as reported by Dun & Bradstreet. Available for corporates only.
Employees	Count	Number of employees as reported by Dun & Bradstreet. Available for corporates only.
SME	Categorical	Indicator variable; an entity is a small and medium-sized enterprise (SME) if all members of the family have annual sales lower than $50m and less than 250 employees, $ESiz$. Available for corporates only.
Panel C: bank characteristics		
Coverage length	Count of months	Number of months covered by the bank.
Country-Region	Categorical	The country or region of bank's headquarters.

Table 2: Summary statistics

This table provides summary statistics for variables defined in Table 1.

Variable	Unit	N	Mean	Std. Dev.	p25	Median	p75	Skew.	Kurt.
Panel A: bank observation characteristics									
PD estimate	Decimals	4,880,497	0.0066	0.0210	0.0005	0.0013	0.0046	11.7	222.5
PD estimate in logs	Log decimals	4,880,497	-6.41	1.57	-7.60	-6.65	-5.38	0.4	2.8
Panel B: entity characteristics									
Depth	Count	1,745,877	2.8	1.7	2.0	2.0	3.0	4.3	29.3
% Foreign contributors	Percentage	1,745,877	0.6	0.3	0.5	0.5	1.0	-0.3	2.1
Mean PD	Decimals	1,745,877	0.0057	0.0140	0.0005	0.0014	0.0053	9.4	158.3
Mean PD in logs	Log decimals	1,745,877	-6.36	1.49	-7.62	-6.57	-5.23	0.4	2.4
Dispersion	Log decimals	1,745,877	0.69	0.48	0.35	0.61	0.94	1.3	6.4
Region	Categorical	1,745,877	42% Europe, 39% North America, 12% Asia Pacific, 4% Africa, 3% Other						
Country	Categorical	1,745,877	30% United States, 20% United Kingdom, 7% Luxembourg, 7% Canada, 4% Germany, 3% South Africa, 3% Ireland, 2% Australia, 2% France, 2% Hong Kong, 2% Italy, 18% Other						
Entity type	Categorical	1,745,877	42% Funds, 40% Corporates, 17% Financials, 1% Government						
SP	Numerical rating	168,088	9.0	3.5	7.0	9.0	11.0	0.2	2.6
Public	Categorical	1,675,714	9.7% Public, 90.3% Private						
Industry	Categorical	697,790	29% Industrials, 20% Consumer Services, 15% Consumer Goods, 11% Basic Materials, 8% Oil & Gas, 6% Utilities, 5% Technology, 4% Health Care, 2% Telecommunications						
Sales	$m	654,842	3,046	13,663	4	104	1,111	13.4	289.5
Employees	Count	654,842	7,093	37,356	20	244	2,305	27.7	1377.2
SME	Categorical	697,790	78% Large, 19% SME, 3% Unclassified						
Panel C: bank characteristics									
Coverage length	Count of months	28	47	9	42	53	54	-0.9	2.3
Country-Region	Categorical	28	21% United States, 21% Africa, 19% United Kingdom, 14% Continental Europe, 14% Canada, 11% Asia Pacific						

4.1 Determinants of dispersion of bank-specific PD estimates

Analysis of drivers of dispersion aims to indicate which entities are most prone to bank's disagreement. In the prior literature, dispersion was for this purpose defined as standard deviation of banks' (log) PD estimates (Berg and Koziol, 2017) or differences in ratings (Carey, 2002). The studies consider entity's credit quality and size, number of bank relationships, whether the entity is a public company, region and industry classification, and loan-specific information (seasoning and draw-down rate). The results are rather ambiguous: Berg and Koziol (2017) show that dispersion is larger for low credit quality borrowers and for larger loans, while Carey (2002) shows that rating disagreements are less likely for large borrowers. Berg and Koziol (2017) argue that bank's subjective analysis is more important for larger borrowers and creates space for disagreement, whereas small borrowers are usually assessed using a standard set of information. Carey (2002), on the other hand, mentions easier access to information and more scrutiny for large borrowers, making them less likely to be misrated. In their analyses, region and industry classifications, as well as private vs public indicators are not statistically significant predictors.

We use rather detailed entity characteristics, including entity's type, size, industry classification, region of risk and credit information: average credit risk and the number of contributing banks with an active credit exposure to the entity. Industry classification and size are examined for corporates only. Entity type (funds, corporates, financials, governments) is particularly interesting in the analysis as it has not been assessed before and may provide good insight into the differences between the individual credit risk models.

Our model is defined as

$$\begin{aligned} D_{i,t} &= \beta_1 \cdot lnPD_{i,t}^{GMean} + \beta_2 \cdot EDep_{i,t} + \\ &\quad \gamma_1 \cdot EReg_i + \gamma_2 \cdot ETyp_i + \gamma_3 \cdot EPub_{i,t} + (\gamma_4 \cdot EInd_i + \gamma_5 \cdot ESiz_{i,t}) + FE_t + \epsilon_{i,t} \\ &= \beta \cdot Credit_{i,t} + \gamma \cdot EChar_{i,t} + FE_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $Credit_{i,t}$ is the credit risk-related information, represented by $lnPD_{i,t}^{GMean}$, the credit risk of entity i at time t (in logs), and $EDep_{i,t}$, the depth of the entity-level information (used as both an integer and a categorical variable in line with the non-linearity of the relationship described by Berg and Koziol, 2017). Analogously, $EChar_{i,t}$ jointly marks the entity characteristics and consists of $EReg_i$, a categorical variable representing entity's region of risk; $ETyp_i$, entity type (both time-invariant); $EPub_{i,t}$, a binary variable identifying public entities; $EInd_i$, entity's industry classification; and $ESiz_{i,t}$, entity's size. The latter two are available only for corporates, for which we run a separate set of regression models. Finally, to capture time dependency we also include time-driven fixed effects FE_t.

Size is a binary variable distinguishing large corporates with more than 250 employees and/or sales above $50 million vs small and medium corporates (SME). We also considered using turnover and number of employees as continuous explanatory variables or grouping them into several categories by size, but neither of these proved more insightful than a simple binary indicator.

The model is estimated using a linear regression with a continuous dependent variable. To correct for the possible cross-sectional correlation, implying that credit risk estimates for a single entity in two subsequent quarters are not independent, we report standard errors clustered at the borrower level.

Ratings provided by credit rating agencies are frequently used as inputs in banks' internal credit risk models, entering the process as both independent variables and also as dependent variables in so-called rating replicator models. Hence, they are expected to act as an anchor of the credit risk estimates and reduce the disagreement between banks. Further, we argue that banks are generally not in consensus when it comes to disagreeing with a rating agency, meaning that dispersion increases with the difference between the credit rating agency's rating and the mean PD. Carey (2002) investigates such an impact of agency rating availability on rating disagreement across banks but does not find it statistically significant.

To connect the PDs to ratings, we use a 21-notch scale mapping PDs to agency-like notches derived from banks' internal scales. We add the rating agency variables to the disagreement determinants model defined in Equation 3 as

$$D_{i,t} = \beta \cdot Credit_{i,t} + \gamma \cdot EChar_{i,t} + \delta_1 \cdot CRA_{i,t} + \delta_2 \cdot CRADist_{i,t} + FE_t + \epsilon_{i,t} \tag{4}$$

where $Credit_{i,t}$ and $EChar_{i,t}$ cover all variables used in Equation 3, $CRA_{i,t}$ is a binary variable indicating if entity i is rated by a credit rating agency (CRA) at time t (1 stays for rated entities and 0 for unrated entities), and $CRADist_{i,t}$ measures the absolute distance between the entity's credit risk as estimated by banks and the rating provided by a credit rating agency in notches. We use ratings from S&P. Again, the reported standard errors are clustered at the entity level to account for cross-sectional correlation.

4.2 The effect of location

The global data allow us to investigate if banks' location – specifically their geographical proximity to an assessed entity – has any impact on dispersion of the associated credit risk estimates. In their analysis of US syndicate loans, Plosser and Santos (2014) distinguish between US and non-US lenders and find that bank's location does in some cases affect the deviation of bank's PD estimates from the median risk. We extend their analysis through worldwide geographical coverage and by including bank and entity characteristics in the model. We argue that banks have information advantage in their domicile country and are able to assess credit risk of local entities more accurately as a result, whereas they tend to deviate from the true risk value for foreign exposures. This is then reflected in dispersion of bank estimates, which should increase with the number of foreign banks with exposures to a given entity.

To analyse this presumption we first define the share of bank contributions that come from foreign banks, $Foreign_{i,t}$, as the ratio of foreign to all bank contributions, where foreign contributions come from banks with headquarters in a different country/region than that of the assessed entity. The geographical classification combines countries and regions and its granularity is determined by bank clusters; if there is a larger group of banks from a single country, we list the country, otherwise we use the broader region to increase overlap between banks and to protect their anonymity.

The variable is used as an addition to the baseline model of dispersion with credit information and entity characteristics as explanatory variables (see Equation 3). We also add an interaction term for $Foreign_{i,t}$ and the binary variables indicating regions.

$$D_{i,t} = \beta \cdot Credit_{i,t} + \gamma \cdot EChar_{i,t} + \delta_1 \cdot Foreign_{i,t} + \delta_2 \cdot (Foreign_{i,t} \times EReg_i) + FE_t + \epsilon_{i,t} \tag{5}$$

As an additional robustness check we look at the absolute difference between individual bank's PD estimate and the mean PD in relation to the credit risk information, entity and bank characteristics. We define a binary variable, $BankForeign_{i,t,b}$, which takes value of 1 if bank b is a foreign contributor to entity i at time t and 0 otherwise. We use time fixed effects FE_t and banks' fixed effects FE_b (Equation 6) or country-region binary variables (Equation 7), which would reveal any systematic differences between regions.

$$\begin{aligned} abs(lnPD_{i,t,b} - lnPD_{i,t}^{GMean}) = \beta \cdot Credit_{i,t} + \gamma \cdot EChar_{i,t} + \delta_1 \cdot BankForeign_{i,t,b} + \\ FE_t + FE_b + \epsilon_{i,t,b} \end{aligned} \tag{6}$$

or

$$\begin{aligned} abs(lnPD_{i,t,b} - lnPD_{i,t}^{GMean}) = \beta \cdot Credit_{i,t} + \gamma \cdot EChar_{i,t} + \delta_2 \cdot BReg_b + \\ \delta_3 \cdot (BankForeign_{i,t,b} \times BReg_b) + FE_t + \epsilon_{i,t,b} \end{aligned} \tag{7}$$

Note that while the model in Equation 6 is very similar to that in Equation 8, here the bank and country-region fixed effects capture the average absolute deviation from the mean. This factors in both systematic and idiosyncratic variation and we thus expect to obtain different results than in the investigation of the systematic factor in the next section.

4.3 Idiosyncratic versus systematic differences

The differences in entity's PD estimates from different banks can be of two types, both of which can apply at the same time: systematic and idiosyncratic. Systematic differences arise from an underlying bias in banks credit risk models, resulting in the bank systematically assigning lower or higher PD estimates to all entities. On the contrary, idiosyncratic differences are driven by entity-specific factors and are not consistent across bank's portfolio.

Critically, idiosyncratic differences should not, on average, adversely impact capital requirements as they cancel out at the aggregate level. On the other hand, systematic differences can cause capital requirements for the same portfolio to differ across banks. While the former may be appreciated by regulators as a sign of banks' individual and independent opinions that can limit herding behaviour, systematic differences are problematic as they make capital requirements incomparable.

The contribution of systematic and idiosyncratic factors can be estimated by looking at the deviation of bank-entity PD estimates from the entity's mean credit risk. If the differences are purely systematic, each bank-entity observation can be calculated as a combination of the entity's mean PD and bank time-specific fixed effects. If all differences are idiosyncratic, the bank time-specific fixed effect have no explanatory power in the model.

Plosser and Santos (2014) and Berg and Koziol (2017) investigate the issue for US syndicate loans lenders and German IRB institutions, respectively, and both studies find significant systematic deviations, with fixed effects explaining 14% and 5% of the overall variation in banks' PD estimates, respectively. This means that a large part of PD estimate variation is idiosyncratic. However, the individual fixed effects are significant and large in magnitude. Plosser and Santos (2014) show that individual banks report PDs that, on average, deviate by -25% to 69% from the median PD, i.e. that PD estimates from one bank are 69% higher than the median on average. Berg and Koziol (2017) find such deviation to be within the -30% to 41% range and conclude that using average risk weights instead of the internal estimates leads up to ±10% differences in the reported regulatory capital ratio for 10 largest banks in their sample.

There are further interesting question not tackled by the previous literature. Banks mostly differentiate their models at least by the entity type of the entities. Are the systematic effects the same for all the models? Does the size of the systematic deviation differ across regions? The richness our dataset allows us to analyse these the systematic factors for both different entity types and different regions.

Our model investigates the impact of bank fixed effects on the deviation of banks' PD estimate from the mean PD, calculated as

$$lnPD_{i,t,b} - lnPD_{i,t}^{GMean} = FE_{t,b} + \epsilon_{i,t,b}. \tag{8}$$

We again report entity-level clustered standard errors due to the potential cross-sectional correlation. The level of idiosyncraticity is measured by the R-squared (0% for purely idiosyncratic dispersion across banks and 100% for purely systematic dispersion). We also show the size distribution and significance of the individual fixed effects to analyse the size of the systematic effect.

We estimate the model using entity type-specific sub-samples to answer the question on differences across multiple internal models. The differences across country-regions are analysed using the average absolute fixed effects for banks domiciled in the given location. Larger average absolute fixed effects mean that banks in the given country-region show larger systematic bias in their PD estimates, we account for positive and negative bias in the same way.

The analysis focuses on a specific time sub-sample of the data – December, March, June and September 2018-2020 – to limit the computational requirements. The regression accounts for 303 bank-months fixed effects.

4.4 COVID-19 crisis effects

The COVID-19 pandemic offers a unique opportunity to evaluate banks' reaction to an unprecedented crisis and the associated high levels of uncertainty. We can make an initial assessment from Figure 2 presented in Section 3, which shows a modest increase in both PD and dispersion in 2020. However, the trends reflect changes in PD estimates as well as in banks' portfolios, which are expected to be more substantial as banks will adjust their portfolios in times of a crisis. To adjust for portfolio changes, we focus on month-on-month percentage changes in the mean PD and dispersion based on a fixed set of PD estimates. For example, if five banks contributed to entity A at time 1 and only four of them contribute at time 2, we would use PD estimates from only the four remaining banks that contributed at both times to calculate the changes in mean PD and dispersion between times 1 and 2. Formally:

$$\begin{aligned} Change\_Fixed\_PD_t^{GMean} &= \frac{Fixed\_PD_{t,ft}^{GMean}}{Fixed\_PD_{t-1,ft}^{GMean}} - 1 \\ &= \frac{exp(\sum_{i=1}^{e_{ft}} \frac{\sum_{b=1}^{n_{i,ft}} lnPD_{i,t,b}}{EDep_{i,ft}} / ECount_{ft})}{exp(\sum_{i=1}^{e_{ft}} \frac{\sum_{b=1}^{n_{i,ft}} lnPD_{i,t-1,b}}{EDep_{i,ft}} / ECount_{ft})} - 1, \end{aligned} \tag{9}$$

where $b \in \{1, \ldots, n_{i,ft}\}$ denotes banks with PD estimates available for both time t and $t-1$ and $EDep_{i,ft}$ is the number of such banks. Similarly, $i \in \{1, \ldots, e_{ft}\}$ denotes entities for which data are available at both time periods and $ECount_{ft}$ is their count. An analogous calculation is defined for dispersion. Subsequently, the monthly changes are cumulated to form an index with January 2018 as the base month.

5 Results

5.1 Determinants of dispersion of bank specific PD estimates

Table 3 shows univariate analysis of dispersion of bank-specific PD estimates, including a breakdown of both mean PD (column 1) and PD dispersion (column 2) as defined by Equations 1-2. It shows that dispersion decreases with credit quality, while the link to depth is not monotonic. However, this might be linked to the fact that Funds tend to have higher dispersion and lower depth than other entities. We take this into account in the regression analysis presented below.

There is no clear time trend; the differences in dispersion observed between 2016 and 2018 are most probably driven by the changing sample of contributing banks. On the other hand, dispersion is significantly affected by entity types and regions: average dispersion for Funds is 0.75 compared to 0.64 for Governments, and dispersion for Europe is 0.72 compared to 0.65 for Asia-Pacific. All of these differences are statistically significant but they might again be linked to the composition of the analysed portfolio in different regions, which is considered in the regression analysis.

Public entities show, on average, lower dispersion than private ones, likely reflecting inequality in information accessibility, similar to entities rated by S&P, which show lower dispersion than those without an external rating, and SMEs, which tend to have higher dispersion than large corporates. In other words, banks tend to provide more consistent PD estimates for entities with more available information. Further, dispersion is higher for entities with worse S&P rating, which is in line with the relationship observed for credit quality given by mean PD.

Finally, there are significant differences across industries, with Utilities showing the lowest level of dispersion and Oil & Gas the highest, which could be driven by the underlying credit quality of the industries: Utilities have the lowest mean PD (0.0050) while Oil & Gas the highest (0.0117).

The multivariate analysis, described in Tables 4 for all entities and 5 for corporates only, then mostly confirms the findings. The relationship between dispersion and depth proves to be non-monotonic even after accounting for the entity type. Funds show significantly higher dispersion compared to Corporates and the difference implied by the regression analysis is higher than observed in the univariate analysis due to adjustments for mean PD and depth. On the other hand, the regional differences change after factoring in all other variables as the inherent variation in banks' portfolios is minimised: dispersion is largest for entities in Europe and Latin America and lowest for African, Middle East and North American entities.

Models estimated only on corporate data reveal the same relationship between dispersion, mean PD and public company identifier. The link between dispersion and depth is weaker and there are no major regional differences with the exception of higher dispersion in Latin America. The analysis shows that the large dispersion observed in the Oil & Gas industry is driven mainly by the large mean PD and becomes comparable to other industries once this is factored in. Entities in Utilities, Technology and Telecommunication have lower dispersion than in other industries.

Further, we look at the dependence of dispersion on ratings from credit rating agencies. Contrary to findings by Carey (2002), our regression results show a significant impact of S&P rating on dispersion of banks' PD estimates (see Table 6), confirming that external ratings serve as anchors for banks and lead to lower dispersion. Further, dispersion increases with difference between banks' credit quality estimate and the agency's rating, i.e. banks do not tend to find another "true" credit risk level if they disagree with the credit rating agency. Both S&P variables have very large t-statistics and the reduction in dispersion for rated entities is up to 0.17 compared to the dispersion interquartile range of 0.35 to 0.94. The impact on dispersion turns to positive when the distance between mean PD-based rating and S&P rating is three or more notches (e.g. aa+ vs a+).

5.2 The effect of location

Portfolios of the analysed banks are typically global, allowing us to investigate the performance of internal PD estimates for local vs foreign entities. Analysing connections between banks and entities in different regions, we find that Africa is the most detached region as 70% of African banks' portfolios are locally focused and 61% of African entities are covered only by local banks. Canada is closely linked with the US; Canadian banks have 64% of their exposures south of the border and 66% of PD estimates for Canadian entities come from either of the two countries. Asia-Pacific, Europe (excl. the UK), United Kingdom and United States are all closely connected.

Table 7 shows the impact of foreign contributions on PD dispersion. The first column shows a baseline model equivalent to that in the last column of Table 4, with a slightly updated regional classification matching that of banks. This change has a very limited impact on the results, with most of the coefficients virtually unaffected. In the second column we introduce the percentage of foreign contributions to an entity into the model. The variable has a positive and significant coefficient, meaning that entities with a greater share of contributions from foreign banks tend to have higher dispersion. At the same time, the changes in region coefficients signal a variance in the impact across regions. Hence, in the third column we model region-specific interactions, showing that the effect is significant only for Asia-Pacific, Europe and United States.

As an alternative point of view, we look at the problem from bank's perspective and analyse the absolute difference between individual bank's PD estimate and the mean PD as shown in Table 8. Again, the first column shows a baseline model for comparison. In the second column we add bank's region as an explanatory variable (but do not reflect whether the bank and entity are in the same region), showing that British banks' PD estimates deviate the most on average, whereas estimates from Asia-Pacific and Canadian banks are closest to the mean PD. In the third column we analyse whether being from the same country as the analysed entity matters, clearly showing that the PD deviation is indeed higher for foreign entities. Lastly, in the fourth column we show that this effect is again not equivalent across the globe, with banks in US, Asia-Pacific and Europe showing the biggest difference in deviation for local and foreign entities.

To sum up, entity's PD dispersion increases with the share of foreign contributors for entities in Asia-Pacific, Europe and United States, and, equally, banks from Africa, Asia-Pacific, Europe and United States produce less accurate ratings for foreign entities. Further investigation (details not reported) shows that US banks report highest PD deviation in the Asia-Pacific region and in Europe, European banks in the US, African banks in Europe, and Asia-Pacific banks in the US.

5.3 Idiosyncratic versus systematic differences

We measure the contribution of systematic versus idiosyncratic factors in differences of banks' PD estimates using the R^2 statistic in regression of PD estimate deviation from the mean PD on bank-time fixed effects. The greater is the R^2 statistic, the more variance in bank's PD estimates can be explained by systematic factors. Further, the size and significance of the fixed effect coefficients provides additional information for individual banks. If a coefficient is significantly different from zero, the given bank reports systematically biased estimates compared to mean PD in the given month. The size of the average difference between bank's PD estimates and mean PD is measured by the size of the coefficient.

Figure 3: Explanatory power of bank fixed effects over time

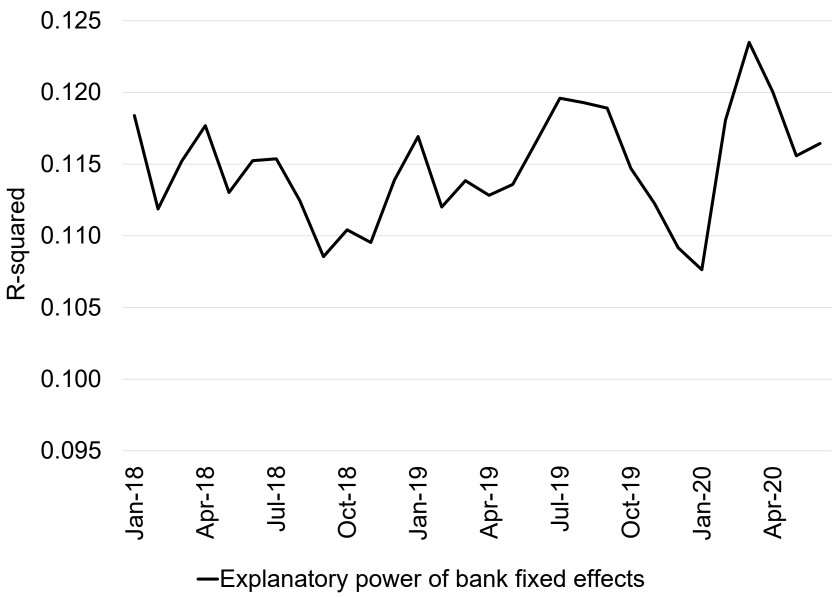
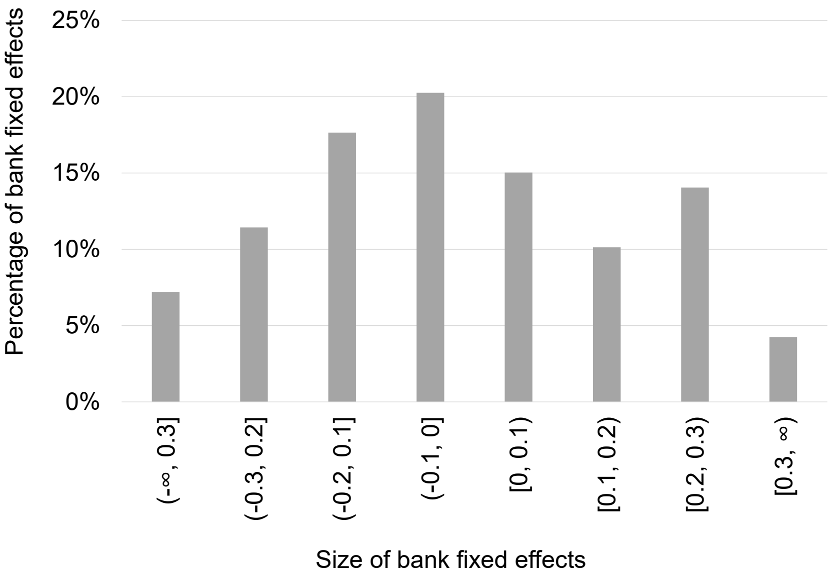


Figure 3 tracks the R^2 statistic over time starting in January 2018, when the sample of contributing banks stabilised. It shows that the systematic effects can explain around 11.5% of the differences in PD estimates and that it has no time trend. The figure is higher than the 5% observed by Berg and Koziol (2017) but broadly in line with the 14% estimated by Plosser and Santos (2014). However, in line with the results presented above and in addition to the analysis in the prior literature, our data show that the contribution of systematic factors varies across entity types. For Corporates, the systematic effects explain just 7.7% of the variation, increasing to 10.1% for Financials and 27.2% for Funds. That is, credit risk modelling for Funds is most impacted by systematic differences and is thus the most problematic from the regulatory perspective. Following discussions with bank practitioners, this may be driven by under-financing of teams focusing on Funds, availability and quality of data, and by the very low number of observed defaults in the Funds space.

Looking at the actual size of the fixed effects (see Figure 4), which imply the magnitude of systematic differences, the coefficients range from -0.39 to 0.41 and 236 out of the 303 fixed effects are significant at 0.1% level. Again, there are significant differences in the size of the coefficients across entity types. Reporting on coefficients in absolute values, 9% of Corporates coefficients are larger than 0.3 and the percentage increases to 17% for Financials and 37% for Funds.

The dataset used in this study does not include information on exposure so we cannot calculate the exact impact on risk-weighted assets. Berg and Koziol (2017) note that the average elasticity of a typical corporate portfolio is 30%, i.e. a 100% increase in a PD estimate causes a 30% increase in the associated capital requirements. Using the same logic on our Corporates results, i.e. multiplying the PD fixed effect by 30% to get the capital requirements impact, the capital requirements could change

Figure 4: Distribution of bank fixed effects



by as much as ±12% and by at least ±6% for 34% of the bank-months. A ±6% difference means that a bank reporting capital ratio of of 8.0% based on its internal PD estimates would report a ratio between 7.5% and 8.5% using the mean PD instead. The impact of PD changes on risk-weighted assets is more significant for lower PDs (Plosser and Santos, 2014), which further exaggerates the possible issues with Funds given their low mean PD.

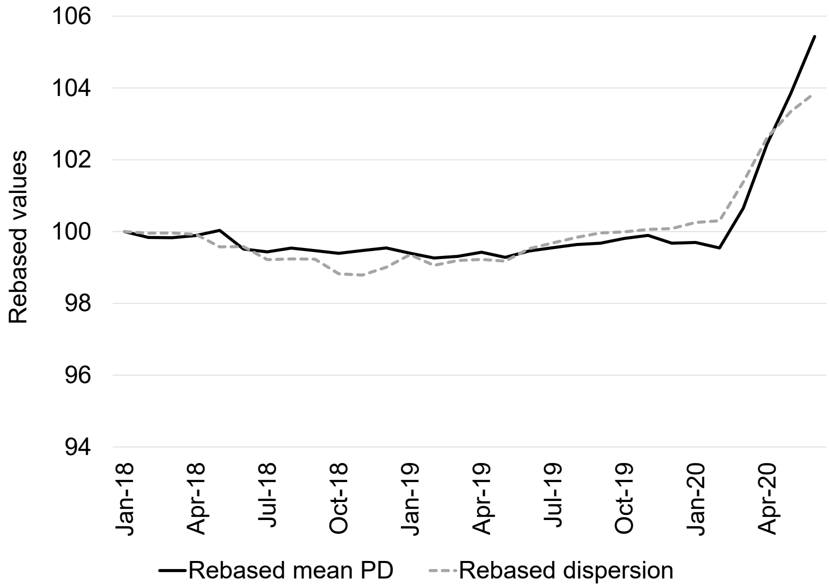
Finally, we summarise the fixed effects by banks' country/region. Table 9 shows the average absolute fixed effect together with Z-scores for two-population mean comparison, differences significant at the 95% confidence level are in bold. European and Canadian banks stand out as those with the largest average absolute fixed effects, results for the other regions are very similar. Looking specifically at Corporates (details not reported), Asia-Pacific and United Kingdom then have the lowest average absolute fixed effects (less than 0.1), with all other country-regions being significantly higher and above 0.15.

5.4 COVID-19 crisis effects

Although the impact of the COVID-19 pandemic on the mean PD in the dataset may appear relatively small as depicted in Figure 2, this may be misleading due to the hidden changes in banks' portfolios. Looking at Table 10, the average percentage of observations dropped each month rose sharply in 2020 compared to the 2018-2019 period, increasing from 2.3% to 4.7% on average. What is more, the average share of new additions decreased from 3.8% to 3.3%. Factoring in such portfolio changes, the full impact of the COVID-19 crisis is revealed in Figure 5.

Compared to the rather constant trends in 2018 and 2019, the average mean PD increased by more than 5.8% in the first 6 months of 2020. While such an increase in credit risk is to be expected during economic recession, our analysis further shows that the average dispersion has increased by 3.8%, implying that banks do not react to the crisis in the same way. In fact, the impact is not equivalent for entity types and industries either; the average mean PD for Corporates increased by 13%, whereas it increased by only 4% for Financials, and remained stable for Funds, with equivalent results for dispersion as summarised in Table 11. Looking at industries, there was a large increase in

Figure 5: Changes in mean PD and dispersion in 2020



the mean PD for Oil & Gas (29%) and Consumer Services (23%), while Telecommunications remained stable. This supports the theory of industry-specific credit cycle suggested by e.g. Stepankova (2021), Nickell et al. (2000) or Frydman and Schuermann (2008).

6 Conclusion

Financial institutions can greatly benefit from use of internal credit risk models for regulatory purposes, increasing the overall process efficiency of the system and reducing burden put at the regulatory authorities at the same time. However, given the uncertainty inherent to credit risk predictions and the incentive to get favourable results, there is a risk that the models will not provide the performance desired by regulators. That is, banks may be motivated to exploit their discretion and optimise the inputs to the models as well as model calibration as argued by Behn et al. (2016), Plosser and Santos (2014) or Berg and Koziol (2017). Methodology documents are sensitive and shared only with regulators which restricts the assessment of models by external researchers and the comparison across financial institutions overlooked by different regulators. Finally, many regulators do not require full reporting of entity and loan level credit risk information including probability of default or do not fully utilise the data when available. This has recently started to change with projects focused on credit risk data collection and analysis run by some regulators (e.g. AnaCredit by the ECB). All these factors make regulation compliance monitoring challenging. We analyse the model outputs of global banks and measure the model risk, specifically we measure the difference in probability of default estimates provided by multiple banks for a single entity.

Using a unique dataset of 4.9 million probability of default estimates provided by 28 global IRB banks, covering the January 2016 to June 2020 period, we analyse determinants of PD dispersion, including bank and entity characteristics, existence of credit rating provided by an external agency, and bank's geographical proximity to its borrower. Further, we break down the variance in estimates to systematic and idiosyncratic and provide a first look at how the unprecedented COVID-19 financial crunch affected dispersion in PD estimates globally.

In Section 5.1 we first show that, abstracting from other factors, substantial variation exists in PD dispersion across a number of variables. Perhaps most interesting is the scale of differences across entity types and regions that has not been discussed in the literature up to this point. The findings are then confirmed through multivariate analysis and a follow-up analysis of the impact of an entity being rated by an external agency. Here, in contrast to the prior literature, we clearly show how the external rating may serve as an anchor point, reducing dispersion in banks' own credit risk estimates.

Our novel analysis presented in Section 5.2 shows that banks tend to provide more consensual PD estimates for borrowers within the same country/region as their own headquarters, likely as a result of a better knowledge of the broader local economic, societal other conditions as well as better access to information.

Mostly in line with Berg and Koziol (2017) and Plosser and Santos (2014), we show in Section 5.3 that most of the variance in credit risk estimates is attributable to idiosyncratic factors, as only 11.5% of differences in PD estimates can be explained by banks' fixed effects. Consequently, the under- and overshooting of the consensus credit risk estimates by individual banks mostly cancels out at the aggregate level, limiting the overall implications for the financial system as a whole. The outlier in the analysis are funds, where the systematic effects account for almost 30% of differences in banks' PD estimates. This raises a question of comparability of the outputs of fund models and related capital requirements across banks.

The fact that banks do not respond synchronously and/or equally to major changes in credit risk of their borrowers is evident from results shown in Section 5.4. The virtually constant average PD and dispersion in the 2018-2019 period has been followed by a strong increase in both variables since Q1/2020. While the increase in the average PD is to be expected given the steadily rising indebtedness worldwide and the high inherent levels of uncertainty due to the COVID-19 pandemic, the change in PD dispersion indicates that the underlying PD changes have been far from consensual across the contributing banks. The underlying reasons remain unknown at this time and may range from inability to properly assess the true level of credit risk given incomplete, fast-changing and/or uncertain information available to banks not being able to time lag between a change in borrower's situation and the resulting credit risk assessment update, or different guidance by regulators.

References

Alexander, C. and Sarabia, J. M. (2012). Quantile uncertainty and value-at-risk model risk. *Risk Analysis: An International Journal*, 32(8):1293–1308.

Basel Committee on Banking Supervision (2013). Regulatory Consistency Assessment Programme (RCAP). Analysis of risk-weighted assets for credit risk in the banking book. Bank for International Settlements.

Behn, M., Haselmann, R. F., and Vig, V. (2016). The limits of model-based regulation. *ECB Working Paper Series*, 1928.

Berg, T. and Koziol, P. (2017). An analysis of the consistency of banks' internal ratings. *Journal of Banking & Finance*, 78:27–41.

Boucher, C. M., Daníelsson, J., Kouontchou, P. S., and Maillet, B. B. (2014). Risk models-at-risk. *Journal of Banking & Finance*, 44:72–92.

Carey, M. (2002). Some evidence on the consistency of banks' internal credit ratings. In *Credit ratings: Methodologies, Rationale and Default Risk*. Risk Books, London, UK.

Chatterjee, S. et al. (2015). Modelling credit risk. Handbook, Centre for Central Banking Studies, Bank of England, London, UK.

Danıelsson, J. (2002). The emperor has no clothes: Limits to risk modelling. *Journal of Banking & Finance*, 26(7):1273–1296.

Danielsson, J., James, K. R., Valenzuela, M., and Zer, I. (2016). Model risk of risk models. *Journal of Financial Stability*, 23:79–91.

Financial Services Authority (2012). Results of 2011 hypothetical portfolio exercise for sovereign, banks and large corporates. Technical report.

Firestone, S. and Rezende, M. (2016). Are banks' internal risk parameters consistent? evidence from syndicated loans. *Journal of Financial Services Research*, 50(2):211–242.

Frydman, H. and Schuermann, T. (2008). Credit rating dynamics and Markov mixture models. *Journal of Banking & Finance*, 32(6):1062–1075.

Glasserman, P. and Xu, X. (2014). Robust risk measurement and model risk. *Quantitative Finance*, 14(1):29–58.

Jacobson, T., Lindé, J., and Roszbach, K. (2006). Internal ratings systems, implied credit risk and the consistency of banks' risk classification policies. *Journal of Banking & Finance*, 30(7):1899–1926.

Nickell, P., Perraudin, W., and Varotto, S. (2000). Stability of rating transitions. *Journal of Banking & Finance*, 24(1):203–227.

O'Brien, J. M. and Szerszen, P. (2014). An evaluation of bank var measures for market risk during and before the financial crisis. Finance and economics discussion series, no. 2014-21, Federal Reserve Board, Washington, DC.

Plosser, M. C. and Santos, J. A. (2014). Banks' incentives and the quality of internal risk models. Staff report no. 704, Federal Reserve Bank of New York, New York, NY.

RMA Capital Working Group (2000). EDF estimation: a 'test-deck'exercise. *RMA Journal*, pages 54–61.

Stepankova, B. (2021). Bank-sourced credit transition matrices: Estimation and characteristics. *European Journal of Operational Research*, 288(3):992–1005.

Table 3: Determinants of dispersion of bank specific PD estimates - uni-variate analysis

The table reports results of uni-variate analysis on both mean PD ($lnPD^{GMean}$) and dispersion (D), which are defined by Equations 1 and 2. The variables are defined in Table 1. T-values are based on Welch adjusted standard errors. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Variable	Mean PD	D	Count	Variable	Mean PD	D	Count
Credit quality (quantiles)				**Public**			
1 (low PD)	0.0003	0.68	349,288	1 Public	0.0075	0.59	163,592
2	0.0006	0.69	349,063	2 Private	0.0052	0.71	1,512,122
3	0.0015	0.64	349,175	**Difference (2-1)**	**-0.0023**	**0.12**	
4	0.0043	0.71	349,178	**t-value**	**-55.5**	**116.1**	
5 (high PD)	0.0218	0.75	349,173		***	***	
Difference (5-1)	**0.0215**	**0.07**					
t-value	**501.7**	**59.9**					
	***	***					
Depth				**SP Rating**			
1 2 observations	0.0065	0.69	1,098,957	1 Rated	0.0081	0.56	168,088
2 3 obsevations	0.0046	0.74	357,927	2 Unrated	0.0054	0.71	1,577,789
3 4 obsevations	0.0044	0.70	137,867	**Difference (2-1)**	**-0.0027**	**0.15**	
4 5+ obsevations	0.0037	0.64	151,126	**t-value**	**-54.0**	**161.2**	
Difference (4-1)	**-0.0028**	**-0.05**			***	***	
t-value	**-104.4**	**-57.8**					
	***	***					
Time period				**S&P rating**			
1 2016	0.0046	0.66	213,294	1 AAA to A-	0.0009	0.52	59,159
2 2017	0.0058	0.68	330,175	2 BBB+ to BBB-	0.0026	0.53	58,460
3 2018	0.0057	0.71	454,913	3 BB+ to B-	0.0202	0.64	48,762
4 2019	0.0057	0.70	506,206	4 CCC+ to C	0.0998	0.78	1,707
5 2020	0.0066	0.70	241,289	**Difference (4-1)**	**0.0989**	**0.26**	
Difference (4-1)	**0.0010**	**0.05**		**t-value**	**57.4**	**18.7**	
t-value	**31.8**	**39.5**			***	***	
	***	***					
Entity Type				**SME**	Corp. only		
1 Funds	0.0015	0.75	734,733	1 Large	0.0086	0.64	543,849
2 Corporates	0.0098	0.65	697,790	2 SME	0.0139	0.70	131,178
3 Financials	0.0065	0.66	287,447	**Difference (2-1)**	**0.0054**	**0.06**	
4 Government	0.0073	0.64	25,907	**t-value**	**96.8**	**37.7**	
Difference (1-2)	**-0.0083**	**0.10**			***	***	
t-value	**-382.4**	**119.8**					
	***	***					
Region (Top 4)				**Industry**	Corp. only		
1 Europe	0.0054	0.72	744,564	1 Basic Materials	0.0093	0.68	72,540
2 North America	0.0050	0.68	680,511	2 Consumer Goods	0.0087	0.65	104,816
3 Asia-Pacific	0.0049	0.65	205,014	3 Consumer Services	0.0109	0.66	141,807
4 Africa	0.0149	0.68	67,956	4 Health Care	0.0105	0.63	28,227
Difference (3-1)	**-0.0004**	**-0.07**		5 Industrials	0.0097	0.66	204,545
t-value	**-18.0**	**-55.4**		6 Oil & Gas	0.0117	0.69	55,028
	***	***		7 Technology	0.0115	0.62	34,028
				8 Telecommu.	0.0101	0.60	15,670
				9 Utilities	0.0050	0.56	41,129
				Difference (9-6)	**-0.0067**	**-0.13**	
				t-value	**-52.8**	**-43.1**	
					***	***	

Table 4: Determinants of dispersion of bank specific PD estimates - multi-variate analysis

The table provides regression results of dispersion (D) on credit-related information and entity characteristics as defined by Equation 3. Mean PD is used in logarithm. All coefficients need to be interpreted in relation to the baseline category. Regressions include time fixed effects. T-values based on robust standard errors clustered at the entity level are reported in brackets. ***, **, *, + denote significance at the 0.1% , 1%, 5% and 10% level, respectively.

Variables	D		D		D		D		D		D	
Mean PD	0.02	***	0.02	***	0.06	***	0.06	***	0.06	***	0.06	***
	(14.3)		(13.8)		(40.6)		(40.4)		(39.8)		(40.3)	
Depth			-0.01	***	0.00		0.00	*	0.00	***		
			(-12.9)		(1.0)		(2.5)		(6.1)			
Depth 2											baseline	
Depth 3											0.06	***
											(17.7)	
Depth 4											0.04	***
											(10.8)	
Depth 5+											0.03	***
											(6.1)	
Corporates					baseline		baseline		baseline		baseline	
Financials					0.05	***	0.05	***	0.05	***	0.05	***
					(9.3)		(9.3)		(8.8)		(8.8)	
Funds					0.22	***	0.23	***	0.22	***	0.22	***
					(43.8)		(44.6)		(41.3)		(40.8)	
Government					0.08	***	0.07	***	0.03		0.02	
					(4.7)		(3.9)		(1.5)		(1.4)	
Africa							baseline		baseline		baseline	
Asia-Pacific							0.03	*	0.02	+	0.03	*
							(2.5)		(1.8)		(2.3)	
Europe							0.06	***	0.05	***	0.05	***
							(6.3)		(4.5)		(4.9)	
Latin America							0.08	***	0.08	***	0.08	***
							(3.8)		(3.6)		(3.8)	
Middle East							0.02		0.02		0.02	
							(0.8)		(0.8)		(0.9)	
North America							0.01		0.00		0.00	
							(0.7)		(-0.5)		(-0.3)	
Is Public									-0.07	***	-0.07	***
									(-13.0)		(-13.6)	
Observations	1,745,877		1,745,877		1,745,877		1,745,877		1,675,714		1,675,714	
R-squared	0.003		0.003		0.030		0.033		0.037		0.039	

Table 5: Determinants of dispersion of bank specific PD estimates for Corporates - multi-variate analysis

The table focuses on Corporates and provides regression results of dispersion (D) on credit related information, entity characteristics and variables specific for Corporates: Industry and Size, as defined by Equation 3. Mean PD is used in logarithm. All coefficients need to be interpreted in relation to the baseline category. Regressions include time fixed effects. T-values based on robust standard errors clustered at the entity level are reported in brackets. ***, **, *, + denote significance at the 0.1% , 1%, 5% and 10% level, respectively.

Variables	D		D		D		D		D	
Mean PD	0.06	***	0.06	***	0.06	***	0.06	***	0.06	***
	(29.0)		(28.0)		(26.3)		(25.1)		(25.2)	
Depth	-0.01	***	0.00	***	0.00		0.00			
	(-5.3)		(-5.2)		(0.5)		(0.8)			
Depth 2									baseline	
Depth 3									0.03	***
									(4.8)	
Depth 4									0.01	
									(1.5)	
Depth 5+									0.00	
									(0.4)	
Basic Materials			baseline		baseline		baseline		baseline	
Consumer Goods			-0.02		-0.02		-0.01		-0.01	
			(-1.5)		(-1.4)		(-1.0)		(-1.0)	
Consumer Services			-0.03	**	-0.03	**	-0.03	*	-0.03	*
			(-2.6)		(-2.7)		(-2.4)		(2.4)	
Health Care			-0.03	*	-0.03		-0.02		-0.02	
			(-2.0)		(-1.5)		(-1.2)		(-1.2)	
Industrials			-0.03	*	-0.03	**	-0.03	*	-0.03	*
			(-2.6)		(-2.9)		(-2.5)		(-2.5)	
Oil & Gas			0.02		0.02		0.02		0.02	
			(1.3)		(1.5)		(1.2)		(1.2)	
Technology			-0.07	***	-0.06	***	-0.05	***	-0.05	***
			(-4.8)		(-4.1)		(-3.8)		(-3.8)	
Telecommunications			-0.07	***	-0.08	***	-0.07	***	-0.07	***
			(-4.1)		(-4.2)		(-4.1)		(4.2)	
Utilities			-0.07	***	-0.07	***	-0.06	***	-0.06	***
			(-4.9)		(-5.0)		(-4.5)		(-4.6)	
Africa					baseline		baseline		baseline	
Asia-Pacific					0.02		0.02		0.02	
					(1.5)		(1.3)		(1.5)	
Europe					0.03	*	0.02		0.02	+
					(2.2)		(1.6)		(1.7)	
Latin America					0.16	***	0.16	***	0.16	***
					(5.2)		(5.1)		(5.2)	
Middle East					0.00		-0.01		-0.01	
					(0.1)		(-0.4)		(-0.3)	
North America					-0.01		-0.02		-0.02	
					(-0.9)		(-1.2)		(-1.1)	
Is Public					-0.05	***	-0.06	***	-0.06	***
					(-8.1)		(-8.3)		(-8.4)	
Is SME							0.01		0.01	
							(1.2)		(1.4)	
Observations	697,790		697,790		647,698		630,868		630,868	
R-squared	0.023		0.025		0.032		0.032		0.032	

Table 6: Dispersion and ratings by S&P

This table provides regression results of dispersion (D) on rating by S&P and credit related information and entity characteristics as defined by Equation 4. Mean PD is used in logarithm. It builds on results presented in Table 4. All coefficients need to be interpreted in relation to the baseline category. Regressions include time fixed effects. T-values based on robust standard errors clustered at the entity level are reported in brackets. ***, **, *, + denote significance at the 0.1% , 1%, 5% and 10% level, respectively.

Variables	Dispersion		Dispersion	
Mean PD	0.06	***	0.06	***
	(40.0)		(39.8)	
Depth 2	baseline		baseline	
Depth 3	0.06	***	0.06	***
	(18.8)		(18.8)	
Depth 4	0.05	***	0.05	***
	(12.7)		(13.0)	
Depth 5+	0.05	***	0.06	***
	(11.5)		(13.3)	
Corporates	baseline		baseline	
Financials	0.05	***	0.05	***
	(8.7)		(8.7)	
Funds	0.21	***	0.21	***
	(38.1)		(38.1)	
Government	0.04	*	0.04	**
	(2.2)		(2.6)	
Africa	baseline			
Asia-Pacific	0.04	**	0.04	***
	(3.1)		(3.3)	
Europe	0.06	***	0.06	***
	(5.8)		(6.1)	
Latin America	0.09	***	0.10	***
	(4.5)		(4.6)	
Middle East	0.03		0.02	
	(1.2)		(1.1)	
North America	0.01		0.01	
	(1.1)		(1.2)	
Public	-0.05	***	-0.05	***
	(-8.6)		(8.1)	
SP Rated	-0.09	***	-0.17	***
	(-15.6)		(-26.3)	
abs(PD^{GMean} to SP in notches)			0.08	***
			(15.1)	
Observations	1,675,714		1,675,714	
R-squared	0.041		0.440	

Table 7: Dispersion and location of bank vs entity

This table measures the impact of contributions by foreign banks on the level of dispersion as defined in Equation 5; it provides regression results of dispersion (D) on percentage of foreign contributors, credit related information and entity characteristics. It builds on results presented in Table 4 and introduces more detailed regions in line with the contributors clusters (UK, US, Canada), Europe marks the other countries in the region in this new regions definition. All coefficients need to be interpreted in relation to the baseline category. Regressions include time fixed effects. T-values based on robust standard errors clustered at the entity level are reported in brackets. ***, **, *, + denote significance at the 0.1% , 1%, 5% and 10% level, respectively.

Variables	D		D		D	
Mean PD	0.06	***	0.06	***	0.06	***
	(39.2)		(39.3)		(38.4)	
Depth 2	baseline		baseline		baseline	
Depth 3	0.06	***	0.06	***	0.06	***
	(17.8)		(16.9)		(16.9)	
Depth 4	0.04	***	0.04	***	0.04	***
	(10.8)		(9.7)		(9.8)	
Depth 5+	0.03	***	0.02	***	0.02	***
	(6.1)		(3.9)		(4.4)	
Corporates	baseline		baseline		baseline	
Financials	0.05	***	0.05	***	0.05	***
	(8.9)		(8.5)		(8.8)	
Funds	0.22	***	0.22	***	0.23	***
	(40.3)		(38.5)		(39.7)	
Government	0.03		0.03		0.03	+
	(1.6)		(1.6)		(1.7)	
Africa	baseline		baseline		baseline	
Asia-Pacific	0.03	*	-0.03	*	-0.08	*
	(2.2)		(-2.0)		(-2.6)	
Europe	0.04	***	0.01		-0.05	**
	(3.6)		(1.2)		(-2.8)	
Latin America	0.08	***	0.02		0.09	***
	(3.8)		(1.0)		(4.0)	
Middle East	0.02		-0.04	+	0.03	
	(0.9)		(-1.7)		(1.3)	
Canada	-0.02	+	-0.04	***	-0.01	
	(-1.7)		(-3.5)		(-0.3)	
United Kingdom	0.06	***	0.06	***	0.07	***
	(5.5)		(5.5)		(5.3)	
United States	0.00		-0.03	**	-0.07	***
	(-0.3)		(-2.6)		(-4.7)	
Is Public	-0.07	***	-0.07	***	-0.07	***
	(-13.1)		(-12.7)		(-11.9)	
% Foreign contributions			0.07	***		
			(10.4)			
% For. c. × Africa					0.04	
					(1.2)	
% For. c. × Asia-Pacific					0.12	***
					(4.0)	
% For. c. × Europe					0.15	***
					(9.7)	
% For. c. × Canada					-0.01	
					(-0.7)	
% For. c. × United Kingdom					-0.01	
					(-0.6)	
% For. c. × United States					0.12	***
					(9.5)	
Observations	1,675,714		1,675,714		1,675,714	
R-squared	0.039		0.040		0.042	

Table 8: Impact of location of bank vs entity on absolute distance of PD estimate from mean PD

This table measures the dependence of absolute deviation of PD estimate from mean PD on the location of the entity vs the bank as defined by Equations 6-7. It provides additional details to the results presented in Table 7. All coefficients need to be interpreted in relation to the baseline category. Regressions include time fixed effects and some of them include bank fixed as well as specified in the table. T-values based on robust standard errors clustered at the entity level are reported in brackets. ***, **, *, + denote significance at the 0.1% , 1%, 5% and 10% level, respectively.

Variables	Abs. dist.		Abs. dist.		Abs. dist.		Abs. dist.	
Mean PD	0.05	***	0.05	***	0.05	***	0.05	***
	(41.7)		(42.3)		(41.9)		(43.1)	
Depth 2	baseline		baseline		baseline		baseline	
Depth 3	0.06	***	0.06	***	0.06	***	0.06	***
	(25.8)		(25.8)		(25.3)		(25.7)	
Depth 4	0.07	***	0.07	***	0.06	***	0.07	***
	(21.5)		(21.3)		(20.9)		(21.5)	
Depth 5+	0.06	***	0.06	***	0.06	***	0.06	***
	(19.8)		(18.6)		(18.1)		(18.4)	
Corporates	baseline		baseline		baseline		baseline	
Financials	0.04	***	0.04	***	0.04	***	0.04	***
	(11.4)		(10.7)		(11.0)		(10.2)	
Funds	0.17	***	0.17	***	0.17	***	0.16	***
	(41.1)		(44.2)		(40.3)		(43.5)	
Government	0.02	**	0.02	+	0.02	*	0.04	***
	(2.6)		(1.7)		(2.5)		(3.5)	
Africa	baseline		baseline		baseline			
Asia-Pacific	0.00		0.00		0.00			
	(0.3)		(0.3)		(-1.5)			
Europe	0.01		0.01		0.00			
	(1.4)		(1.3)		(0.4)			
Latin America	0.00		0.00		-0.02			
	(-0.0)		(0.4)		(-2.2)			
Middle East	0.02		0.01		0.00			
	(1.5)		(0.7)		(0.3)			
Canada	0.00		0.00		0.00			
	(0.3)		(-0.0)		(-0.4)			
United Kingdom	0.02		0.02	+	0.02	*		
	(1.8)		(1.9)		(2.0)			
United States	-0.01		-0.01		-0.02	*		
	(-1.1)		(-0.7)		(-2.4)			
Is Public	-0.05	***	-0.05	***	-0.05	***	-0.05	***
	(-13.4)		(14.6)		(-13.5)		(14.6)	
Bank - Africa			baseline				baseline	
Bank - Asia-Pacific			-0.06	***			-0.06	***
			(-6.8)				(-5.9)	
Bank - Europe			-0.01	+			-0.02	*
			(-1.7)				(-2.1)	
Bank - Canada			-0.05	***			-0.04	***
			(-6.4)				(-4.8)	
Bank - United Kingdom			0.02	**			0.04	***
			(3.2)				(5.0)	
Bank - United States			-0.01	+			-0.05	***
			(-1.7)				(-6.4)	
Bank foreign					0.03	***		
					(15.4)			
B. f. × Bank - Africa							0.02	+
							(1.9)	
B. f. × Bank - Asia-Pacific							0.03	**
							(2.6)	
B. f. × Bank - Europe							0.03	***
							(5.9)	
B. f. × Bank - Canada							0.00	
							(-0.2)	
B. f. × Bank - United Kingdom							0.00	
							(-1.2)	
B. f. × Bank - United States							0.06	***
							(23.1)	
FE bank	yes				yes			
Observations	4,880,497		4,880,497		4,880,497		4,880,497	
R-squared	0.053		0.038		0.055		0.040	

Table 9: Average absolute fixed effects by country and Z-scores

This table compares average absolute fixed effects across banks' regions estimated based on model presented in Equation 8. The averages are compared using Z-scores for two-population mean comparison. Differences significant at the 95% confidence level are in bold.

	Avg. abs. fixed effects	Z-score Asia-Pacific	Africa	United Kingdom	United States	Canada
Bank - Asia-Pacific	0.12					
Bank - Africa	0.14	0.95				
Bank - United Kingdom	0.14	0.99	0.15			
Bank - United States	0.15	1.49	0.62	0.37		
Bank - Canada	0.18	**2.83**	**2.28**	1.86	1.81	
Bank - Europe	0.21	**3.88**	**3.49**	**2.98**	**3.10**	1.26

Table 10: 2020 impact on portfolio churn

This table presents the monthly percentages of observation being added to or dropped from the observed portfolio.

		N	Mean	p25	Median	p75
2018-2019 new observations	Percentage	24	3.8%	2.1%	2.6%	4.1%
2018-2019 dropped observations	Percentage	24	2.3%	1.8%	2.1%	2.4%
2020 new observations	Percentage	6	3.3%	2.6%	3.0%	3.5%
2020 dropped observations	Percentage	6	4.7%	2.8%	3.1%	6.3%

Table 11: Changes in mean PD and dispersion in 2020 by entity type and industry

This table shows the percentage change in the average mean PD and dispersion between December 2019 and June 2020 for different entity types and industries. The calculation is based on Equation 9.

	Mean PD 6M % change	Dispersion 6M % change
All	5.8%	3.8%
Corporates	13.4%	6.9%
Financials	3.9%	3.4%
Funds	-0.2%	1.1%
Basic Materials	12.5%	7.5%
Consumer Goods	12.3%	5.5%
Consumer Services	23.0%	11.0%
Health Care	5.7%	-0.2%
Industrials	9.9%	7.1%
Oil & Gas	29.0%	8.7%
Technology	5.0%	3.8%
Telecommunications	0.4%	2.1%
Utilities	3.3%	0.8%

IES Working Paper Series

2020

1. Tomas Kucera: *Cognitive Bias Mitigation: How to Make Decision-Making Rational?*
2. Tomas Kucera: *Are Employment Effects of Minimum Wage the Same Across the EU? A Meta-Regression Analysis*
3. Petr Hanzlik, Petr Teply: *Institutional and Other Determinants of the Net Interest Margin of US and European Banks in a Low Interest Rate Environment*
4. Michal Hlavacek, Ilgar Ismayilov, Ayaz Zeynalov: *Reassessment of the Fiscal Multiplier in Developing Countries: Regime-Switching Model*
5. Evzen Kocenda, Karen Poghosyan: *Nowcasting Real GDP Growth: Comparison between Old and New EU Countries*
6. Diana Zigraiova, Tomas Havranek, Jiri Novak: *How Puzzling Is the Forward Premium Puzzle? A Meta-Analysis*
7. Barbora Malinska: *Time-Varying Pricing of Risk in Sovereign Bond Futures Returns*
8. Shahriyar Aliyev, Evzen Kocenda: *ECB Monetary Policy and Commodity Prices*
9. Roman Kalabiska, Michal Hlavacek: *Regional Determinants of Housing Prices in the Czech Republic*
10. Boris Fisera, Roman Horvath: *Are Exchange Rates Less Important for Trade in a More Globalized World? Evidence for the New EU Members*
11. Jana Votapkova: *The Effect of Inpatient User Charges on Inpatient Care*
12. Lenka Slegerova: *Using 'Costs States' in a Semi-Markov Model to Estimate Cost-Effectiveness with an Illustration for Metastatic HER2+ Breast Cancer in the Czech Republic*
13. Periklis Brakatsoulas, Jiri Kukacka: Credit Rating Downgrade Risk on Equity Returns
14. Roman Horvath: *Natural Catastrophes and Financial Development: An Empirical Analysis*
15. Vit Machacek: *Globalization of Science: Evidence from Authors in Academic Journals by Country of Origin*
16. Nino Buliskeria, Jaromir Baxa: *Do Rural Banks Matter That Much? Burgess and Pande (AER, 2005) Reconsidered*
18. Kseniya Bortnikova: *Beauty and Productivity: A Meta-Analysis*
19. Radomir Mach, Milan Scasny, Jan Weinzettel: *The Importance of Retail Trade Margins for Calculating the Carbon Footprint of Consumer Expenditures: A Sensitivity Analysis*
20. Javier Garcia-Bernardo, Petr Jansky, Thomas Tørsløv: *Multinational Corporations' Effective Tax Rates: Evidence from Orbis*

21. Petr Jansky, Andres Knobel, Markus Meinzer, Tereza Palanska, Miroslav Palansky: *Country-by-Country Reporting and Other Financial Transparency Measures Affecting the European Union*
22. Marek Sedivy: *Mortality shocks and household consumption: The case of Mexico*
23. Lydia Chikumbi, Milan Scasny, Edwin Muchapondwa, Djiby Thiam: *Premium Price For Natural Preservatives In Wine: A Discrete Choice Experiment*
24. Roman Horvath: *Peer Effects in Central Banking*
25. Nicholas Tyack, Milan Scasny: *Estimating the Social Value of Specific Crop Diversity Conservation Plans: Do Czechs Care More About Conserving Hop, Wine or Fruit Tree Varieties?*
26. Salim Turdaliev: *Labor Force Participation of Married Woman in Russia*
27. Jaromir Baxa, Michal Paulus: *Exchange rate misalignments, growth, and institutions*
28. Michal Paulus, Jaromir Baxa, Eva Michalikova: *Does Enforcement Of the Rules Against Foreign Bribery Discourage Exports? A Case of the OECD Anti-Bribery Convention*
29. Tomas Havranek, Zuzana Irsova, Lubica Laslopova, Olesia Zeynalova: *Skilled and Unskilled Labor Are Less Substitutable than Commonly Thought*
30. Levan Bezhanishvili, William Appleman, Zurab Abramishvili: *Was the Georgian Policy Shifting Public Sector Working Hours by One Hour "Family Friendly" and Did It Increase Female Labor Participation?*
31. Fan Yang: *A Survey of Empirical Literature on Hedge Fund Performance*
32. Ali Elminejada, Tomas Havranek, Roman Horváth: *A Meta-Analysis of the Frisch Extensive Margin Elasticity*
33. Petra Landovská: *Business cycle sensitivity of Statutory Health Insurance: Evidence from the Czech Republic*
34. Natalia Li: *Estimating the Relationship Between Resource Intensity and Occupational Health and Safety in Kazakhstan*
35. Sophio Togonidze, Evžen Kočenda: *Macroeconomic Responses of Emerging Market Economies to Oil Price Shocks: Analysis by Region and Resource Profile*
36. Olena Chornaa, Lucas van der Veldeb : *Do Women Benefit from Minimum Wages?*
37. Sarah Godar and Petr Janský*: Corporate Profit Misalignment: Evidence from German Headquarter Companies and Their Foreign Affiliates*
38. Leyla Ates, Alex Cobham, Moran Harari, Petr Janský, Markus Meinzer, Lucas Millan-Narotzky, Miroslav Palanský: *The Corporate Tax Haven Index: A New Geography of Profit Shifting*
39. Ichiro Iwasaki, Evžen Kočenda, Yoshisada Shida: *Institutions, Financial Development, and Small Business Survival: Evidence from European Emerging Markets*
40. Laure de Batz, Evžen Kočenda: *Financial Crime and Punishment: A Meta Analysis*

41. Petr Janský: *Corporate Effective Tax Rates for Research and Policy*
42. Svatopluk Kapounek, Zuzana Kučerová, Evžen Kočenda: *Selective Attention in Exchange Rate Forecasting*
43. Vědunka Kopečná, Milan Ščasný and Lukáš Rečka: *Estimating Elasticity of Substitution in CES Production Function: Examining Different Nesting Structures and EU Regions*
44. Barbora Stepankova: *Consistency of Banks' Internal Probability of Default Estimates*

All papers can be downloaded at: http://ies.fsv.cuni.cz.

Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail: ies@fsv.cuni.cz http://ies.fsv.cuni.cz