ZNAČAJ PRIMENE STATISTIČKIH MODELA U RAZVOJU REJTING SISTEMA FINANSIJSKIH INSTITUCIJA

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Apstrakt

Najbitniji sistem za upravljanje rizicima i merenje finansijski performansi jeste rejting sistem. Rejting sistem se smatra integralnim delom bankarskih tekućih poslova i njihove kulture upravljanja rizicima. Sve banke se trude da istaknu tu njegovu pripadnost tekućim poslovima, kako bi pokazali supervizorima neophodnost njegovog korišćenja u svrhu determinisanja zahteva minimalnog regulatornog kapitala.

Komitet u Bazelu za pojedine klase izloženosti rizicima, preporučuje korišćenje osnovne metodologije kod koje bankarske institucije kao ulaznu veličinu koriste sopstvenu procenu rizika neplaćanja dužnika, dok se procene dodatnih faktora rizika primenjuju putem standardizovonih pravila supervizora.

Ova osnovna metodologija je dostupna za bankarske institucije koje imaju mogućnost da svoje supervizore uvere da su one sposobne da odgovore na određene minimalne zahteve bankarskog sistema, proces upravljanja rizika i sposobnost procene njegovih bitnih komponenti.

Takođe pored osnovne metodologije definisane su i napredne metodologije koje pružaju mogućnost unutrašnje procene komponenti rizika. Široka primena navedenih procena je važan deo dinamičkog i risk-senzitivnog IRB

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pristupa (Internal Rating Based). Tako mogu da se identifikuju i razlikuju one bankarske institucije koje imaju sposobnost da sprovedu određenu validnu i kvantifikovanu procenu rizika.

Neki određeni modeli, postupci i procesi procene verovatnoće neplaćanja u određenim situacijama, putem dobijenih rezultata, omogućuju menadžmentu bankarskih institucija detaljno analiziranje realne slike mogućih dužnika što u krajnjem pruža i moguću bolju analizu njihovog difolta.

Ključne reči: *verovatnoća neplaćanja, dužnik, modeli, interni rejting, statistička analiza, adekvatnost bankarskog kapitala.*

JEL: C26, G21

Uvod

Osnovnu bazu determinisanja rejtinga izloženosti riziku ili rejtinga drugih ugovornih strana kod manjeg broja bankarskih institucija, a u okviru određenih portfolia, činio je postupak verovatnoće ispunjenja obaveza ili drugi kvantitativni alati.

Takvi postupci trebalo bi da imaju mogućnost da budu razvijeni od strane isporučioca (vendor) i uglavnom pored kvalitativnih i kvantitativnih faktora (finansijske proporcije), sadrže i stadardizovane faktore (istorija plaćanja, kreditni izveštaji itd). (Bessis J, 2019)

Ovakve alate kod velike korporativne izloženosti, primenjivalo je mali broj bankarskih institucija, dok je nekoliko njih koristilo ove alate u situacijama srednjeg tržišta ili korisnika iz malog biznisa. Kao primer za navedenu situaciju može se navesti korišćenje kreditnih skor modela (kategorije „scorecard", modele difolta, isporučioca (vendor) i konsultanata).

Takođe navedeni modeli imaju u sebi bitne elemente u postupcima procene rizika u velikom broju institucija. Kod konstruisanja banaka, prvo se definišu finansijske zavisne varijable, koje se pojavljuju prilikom pružanja informacionih podataka o procentu verovatnoće neispunjenja obaveza.

Putem uzorka razmatranog kredita, a primenom dostupnih istorijskih podataka, bankarska institucija procenjuje uticaj svake od ovih zavisnih varijabli na postupak neispunjenja obaveza. Utvrđenih koeficijenti procene se dalje koriste na podatke trenutnih zajmova i pojavljuju kao rezultat koji je utvrđen u proceni pitanja procenta verovatnoće neispunjenja obaveza. Rezultat se zatim konvertuje u rejting stepen (realni inputi kod takvih modela su vrlo identični kvantitativnim elementima rizika, utvrđenog od strane procenitelja).

Aktivnosti i procesi koji počivaju na statističkim modelima imaju bitniju ulogu kod manjih korporativnih zajmova nego na tržištima srednje veličine ili kod velikih korporacija.

Pojedine bankarske institucije su zasnovale svoje rejtinge isključivo na statističkim skor modelima difolta i kredita ili specijalnim ciljevima finansijskih analiza, ne uzimajući u obzir jednostavne mehaničke procese. Takci rejtinzi omogućuju dodeljivanje rejtinga radi podešavanja rejtinga na određeni unapred ograničeni stepen koji počiva na faktorima procene. (Brealey R., 2021)

U određenoj situaciji definisanog procesa scorecard definiše stepen, dok procenitelj po ličnoj analizi, može definisati finalni stepen naniže ili naviše i to maksimalno za jedan ili dva stepena.

Pored toga, kvantitativnim i faktorima procene se mogu dodeliti maksimalni poeni što efikasno ograničava uticaj razmatranja određene procene na konačni rejting. Skoro 20% bankarskih institucija primenjuje ovaj koncept u svojim velikim korporacijama, dok se identičan procenat institucija izjasnio da primenjuje ovaj koncept za svoje manje korporacije i srednja tržišta. Stavljanje ograničenja na proceni je profesionalnije kada se te procene isključivo primenjuju za rast rejtinga, a ne za njegov pad. Najveći broj institucija rejtinge dodeljuje primenom najznačajnijih delova procene, gde je relativna značajnost ukazana delovima koji nisu ograničeni.

Regresiona analiza

U statističkom modeliranju, regresiona analiza predstavlja proces statističkih analiza na osnovu kojih se vrši vrednovanje uzajamne povezanosti zavisne ili kriterijumske promenljive i nezavisnih (predikatorskih) promenljivih. (Matz L., 2017)

Dobijeni rezultati na osnovu regresione analize ističu da se vrednosni podatak zavisne promenljive menja sa promenom vrednosnog podatka neke nezavisne promenljive, dok ostali vrednosni podaci nezavisnih promenljivih ostaju nepromenjeni.

Kao stalan zadatak regresione analize pojavljuje se aproksimacija regresone funkcije, pomoću koje se ističe veza između promenljivih zavisnih i nezavisnih. Ova analiza se pored toga koristi i za vrednovanje funkcionalne zavisnosti izmedju pomenutih promenljivih, kao i prirodu tih zavisnosti.

U praksi nas može recimo zanimati zavisnost između zarada zaposlenih i njihovog obrazovanja, stopa i to kamatnih i ponude novca. Da bi se utvrdilo da li postoji zavisnost između određenih pojava i u kojoj meri je njihova zavisnost, neophodno je primeniti određeni model regresije.

Analiza regresije se primenjuje u dve totalno različite svrhe. Najpre se primenjuje za planiranje, prognoziranje i moguće predviđanje, u situacijama u kojima se njeno korišćenje poistovećuje se poljem mašinskog učenja. Zatim se koristi i u situacijama za utvrđivanje uzročno posledičnih veza između zavisnih i nezavisnih promenljivih.

Da bi se uspešno koristila ova vrsta analize za predviđanje, lice koje istražuje treba da oprezno definiše i objasni postojanje uzročne posledične veze između promenljivih odnosno njihovu funkcionalnu vezu. Funkcionalna veza je naročito važna u situacijama u kojima istraživači imaju mišljenje da će se za procenjivanje uzročno posledične veze koristiti samo podaci iz uzorka ili statističkog skupa i odgovarajuće funkcionalne relacije.

Regresiona analiza u finansijskim institucijama

Ključna prednost regresionih modela u finansijskim institucijama je njihova sposobnost da analiziraju složene veze između promenljivih i pruže kvantitativne procene koje podržavaju donošenje utemeljenih poslovnih odluka. (Gitman L., 2019)

Ulazne karakteristike koje nisu značajne za model mogu ozbiljno narušiti kvalitet i stabilnost modela kada se koriste radi predviđanja dužničkog rizika u vezi sa ovim podacima. Poželjno je da se promenljive, koje nemaju veliki uticaj na rezultate modela, jednostavno ignorišu i time pojednostavi model, što u svakom slučaju licima koja vrše regresionu analizu olakšava rad.

Način da se ponesemo sa ovim problemom se nalazi u podeli uzroka na dva dela, gde se jedan deo (uzorak obuke) koristi radi procene modela a drugi deo je hold-out uzorak (ostatak uzorka) koji se koristi kod validacije rezultata.

Konzistentnost rezultata oba uzorka se jednovremeno uzimaju kao indikatori stabilnosti modela.

U finansijskim institucijama regresiona analiza se najčešće se koristi u sledećim slučajevima:

a) Kreditna analiza: Regresijski modeli se koriste za procenu kreditnog rizika klijenata. Modeli poput logističke regresije se koriste za predviđanje verovatnoće da će klijent otplaćivati kredit redovno.
b) Upravljanje aktivom i pasivom: Finansijske institucije koriste regresione modele za predviđanje nivoa depozita i kredita, što im pomaže u upravljanju svojim bilansom i rizicima povezanim sa likvidnošću.
c) Marketinške strategije: Regresiona analiza se koristi za identifikovanje najisplativijih segmenata klijenata i utvrđivanje najdelotvornijih marketinških kanala i kampanja.
d) Prevencija prevare: Regresioni modeli se koriste za otkrivanje sumnjivih transakcija i obrazaca ponašanja koji mogu ukazivati na prevaru.
e) Prilagođavanje cena: Banke koriste regresione modele za određivanje optimalnih kamatnih stopa i naknada zasnovanih na tržišnim uslovima i profilu rizičnosti klijenata.
f) Upravljanje rizicima: Regresioni modeli se koriste za procenu kreditnog, tržišnog i operativnog rizika kojem je banka izložena.

Analiza diskriminante

Analiza diskriminante se vrši na sličan način kao u kod linearnog regresionog modela.

Zapravo proporcije između koeficijenata regresionog modela su jednake sa odgovarajućim proporcijama analize diskriminante. Razlika između ova dva metoda je teorijska: dok u regresionom modelu karakteristike imaju determinističku prirodu, a stanje difolta je slučajna promenljive. Kod analize determinante je sasvim suprotno tj. karakteristike predstavljaju slučajnu promenljivu dok je stanje difolta determinisano. Ove su razlike u praksi virtuelno nevažne.

Možemo zaključiti da su prednosti i mane analize diskriminante putem ovog modela slične onima kod regresionog modela, a to su:

- Analiza diskriminante je široko poznata metoda sa algoritmima procene koji su raspoloživi;
- Kada se jednom koeficijenti procene tada rezultati mogu da se obračunaju direktno kao linearne funkcije;
- Pošto se karakteristike X_i realizuju na osnovu slučajnih promenljivih tada se statistički testovi značajnosti modela i koeficijenata baziraju na pretpostavkama multivarijantne normalnosti. Ovo je međutim nerealno kod promenljivih koje se tipično koriste u modelima rejtinga, kao na primer, kod finansijskih proporcija dobijenih na osnovu bilansa. Stoga su metode analize stabilnosti modela i mogućnosti koeficijenata ograničene u poređenju između uzorka i ostatka uzorka; i
- Apsolutne vrednosti funkcije diskriminante se ne mogu interpretirati po nivoima.

Jedan mogući način dobijanja homoshedastičnih veličina predstavlja izračunavanje procenjenih veličina putem metode najmanjih kvadrata sa težinama (WLS). Iako je ovo moguće to i nije česta praksa zbog toga što, u cilju dobijanja učestalosti difolta, podaci moraju biti grupisani pre izvršenja procene. (Greuning H., 2018)

Grupisanje uključuje značajne praktične probleme kao što su određivanje veličina i broja grupa i način tretmana različitih kovarijanti unutar jedne jedine grupe (Zhou et al., 2024).

Logit i Probit modeli predstavljaju bolji način procene jer ne zahtevaju prethodno grupisanje kao u ML metodu (to je metod maksimalne verodostojnosti - verovatnoće). Kod binomno zavisnih promenljivih funkcija verovatnoće glasi:

$$\mathbf{L(b)} = P(\boldsymbol{b'} \times \mathbf{X_i})^{\mathbf{yi}} \times \mathbf{(1\text{-}P(\boldsymbol{b'} \times X_i)^{1\text{-}yi})} \qquad \mathbf{(1)}$$

Kod probit modela funkcija P predstavlja funkciju normalnog rasporeda verovatnoćaa u Logit modelu ona predstavlja logaritamsku funkciju rasporeda verovatnoća. Putem ove jednačine procena modela je teoretski ubedljiva i jednostavna za rukovanje. (Samuels J., 2016)

Nadalje, ovakav ML pristup nas vodi do širokog seta testova radi evaluacije modela i njegovih promenljivih. Obično se izbor link funkcije ne zasniva na teorijskoj osnovi. Korisnici kojima je bliža upotreba normalnog rasporeda verovatnoća opredeliće se za Probit model.

I stvarno, razlike u rezultatima po obe klase modela su često zanemarljive. To je zbog toga što obe funkcije imaju slične forme osim tail-ova, koje su teže za obračunavanje kod Logit modela. Istina je da je Logit model lakši za rukovanje jer je lakše obračunavanje estimatora (procenitelja).

Međutim složenost proračunavanja danas je često beznačajna pošto najveći broj korisnika upotrebljava statističke softverske pakete gde su algoritmi procene integrisani u softverska rešenja. Važna je i činjenica da se koeficijenti Logit modela mogu lakše interpretirati (Ochuba et al., 2024).

Da bismo to razumeli tranformisaćemo Logit model dat jednačinom (1) na sledeći način:

$$P_i/(1-P_i) = e^{\beta} \times X_i \qquad (2)$$

Na levoj strani jednačine (2) nalaze se odnosi između verovatnoće difolta i verovatnoće preživljavanja (survival).

Sada se lako može videti da varijacija jedne promenljive $\mathbf{x_i}$ u jednoj jedinici ima učinak koji je jednak e^{β} na verovatnoću kada veličina $\boldsymbol{\beta_k}$ koeficijent promenljive $\mathbf{x_i}$.

Transformisani koeficijent $\mathbf{e^{\beta}}$ se zove odnos verovatnoće (adds-ratio). On predstavlja multiplicirani učinak karakteristika dužnika na verovatnoću. Stoga u Logit modelu koeficijent se može interpretirati na verovatan način što nije slučaj u Probit modelu.

Panelni modeli

Do sada opisane metode predstavljaju poprečne metode zbog toga što se sve promenljive odnose na isti vremenski period. Finansijske institucije tipično raspoređuju setove promenljivih na više od jednog perioda kod svakog dužnika. U ovom slučaju moguće je proširiti poprečne inpute podataka na panelske setove podataka.

Na taj način povećavamo broj raspoloživih posmatranja kod procenitelja a takođe povećavamo stabilnost i preciznost rejting modela. Panelni modeli mogu integrisati u sebe i makroekonomske promenljive.

Makroekonomske promenljive mogu poboljšati model iz nekoliko razloga. Najpre mnogi izvori makroekonomskih podataka su ažurniji i dostupniji od mezo i mikro podataka, jer podatke o makroekonomskim promenljivim objavljuje zvanična nacionalna statistika. Na primer, finansijski odnosi obračunati po osnovu bilansnih informacija obično se ažuriraju na godišnjem nivou i nisu stariji od dve godine kada ih koristimo radi procene rizika. (Dowling E.T., 2017)

Cene nafte na primer, su nam na raspolaganju po dnevnoj učestalosti podataka, isto tako cene plemenitih metala, cene akcija na berzama i slično menjaju se više puta u toku dana i mi te informacije možemo dobiti.

Naglašavanjem makroekonomskih inputa u modelu možemo koristiti radi formiranja stress testova kreditnog rizika. Pošto makroekonomske promenljive primarno utiču na apsolutne vrednosti verovatnoća difolta, razumno je inkorporirati makroekonomske impute u ove klase modela kod procenjivanja verovatnoće difolta. (Engeimann B., at.all. 2018)

Na prvi pogled panelni modeli su slični presečnim modelima. Ustvari, mnogi razvojni programeri zanemaruju dinamički obrazac promenljivih i jednostavno ih uključuju u Logit i Probit model. (Alastair L., 2022)

Generalno uzevši poprečni podaci ispunjavaju ovakve zahteve ali panelski podaci ne ispunjavaju iste zahteve, i to stoga što posmatranja istog perioda i posmatranja istog dužnika mogu biti u korelaciji. Uvođenje korelacije u procedure procene je komplikovano. (Mishkin F., 2020)

Na primer, estimator sa fiksnim učinkom koji nam je poznat iz analize panela kod neprekidne zavisne promenljive nije na raspolaganju u Probit modelu. Pored toga, modifikovani estimator sa fiksnim efektom u Logit modelu isključuje sve dužnike koji nisu u difoltu iz analize pa nam se zbog toga čini kao da je neodgovarajući. Na kraju, estimatori sa slučajnim efektom koji su propisani u literaturi mogu biti obračunati samo po osnovu upotrebe specijalizovanih softverskih paketa.

Modeli hazarda

Svi modeli koji su do sada navedeni pokušavali su da ocene rizičnost dužnika putem procenjivanja određenog tipa ili rezultata koji bi indikovao da li dužnik jeste ili nije sklon difoltu unutar specifičnog horizonta predviđanja.

Međutim, nije izvedeno ni jedno egzaktno predviđanje difolta u vremenu. Pored toga ovakvi pristupi ne omogućavaju evaluaciju dužnikovog rizika u budućnosti koji ne bi ušao u difolt u toku jednog referentnog vremenskog perioda.

Ovi nedostaci se mogu prevladati pomoću modela hazarda, koji eksplicitno obrađuje funkciju preživljavanja i sledstveno tome vreme u kome uzimamo u obzir dužnički difolt.

Unutar ove klase modela Coxov proporcionalni model hazarda je najzastupljeniji regresioni model pošto on nije zasnovan na bilo kakvim pretpostavkama koje razmatraju prirodu ili oblik osnovne distribucije preživljavanja.

Model ocenjuje da je utemeljena stopa hazarda (pre nego vreme preživljavanja) funkcija nezavisne promenljive. Ne čini se nikakva pretpostavka o prirodi ili obliku funkcije hazarda. Stoga je Coxov regresioni model ustvari semiparametarski model.

On se može opisati kao: $h_i(t/x_i)= h_0(t) \times e^{\beta \times xi}$ **(3)** , gde veličina $h_i(t/x_i)$ označava rezultirajući hazard koji je zadat prema kovarijatima kod respektivnog dužnika u respektivnom periodu preživljavanja t.

Izraz $h_0(t)$ se naziva osnovna linija hazarda i predstavlja hazard kada su sve nezavisne promenljive jednake nuli. Ako se kovarijati mere kao devijacije u odnosu na njihove respektivne srednje vrednosti tada veličina $h_0(t)$ može biti interpretirana kao stopa hazarda po nekom prosečnom dužniku. Model koji je gore prikazan sadrži važne pretpostavke. Najpre on specificira višestruki odnos između funkcije hazarda i logaritamske linearne funkcije zavisne promenljive koja ukazuje da odnos hazarda kod dva dužnika ne zavisi od vremena tj. da je relativna rizičnost dužnika konstantna odakle potiče ime za Coxov proporcionalni model hazarda.

U ovom modelu se pretpostavlja da je tačka difolta u vremenu neprekidna slučajna promenljiva. Međutim, često se dešava da se finansijski uslovi dužnika ne posmatraju kontinelno (neprekidno) već kao diskretne vrednosti u vremenu. Štaviše, kovarijati su tretirani kao da su konstantni u vremenu dok se, tipične zavisne promenljive kao što su, na primer finansijski odnosi, menjaju tokom vremena.

Iako postoje neki naprednjiji modeli koji sadrže gore pomenute osobine procena u ovakvim modelima postaje kompleksna.

Prednosti i mane modela hazarda mogu se sumarno prikazati kao (Alirezaie et al., 2024):

- Modeli hazarda omogućavaju procenu funkcije preživljavanja za sve dužnike. Vremenski period istorijskih podataka o difoltu je osnova za procenu preživljavanja dužnika i verovatnoću difolta u narednom vremenskom periodu i
- Ovi modeli indirektno procenjuju realne pretpostavke o difoltu u budućem vremenskom periodu.

Neuronske mreže

Neuronske mreže su vrsta računarskog sistema inspiriranog strukturom i funkcijama bioloških neuronskih mreža u mozgu. Glavne komponente neuronskih mreža su (Abrahams et al., 2024a):

- Arhitektura mreže - Sastoji se od međusobno povezanih "čvorova" ili "neurona" koji obrađuju informacije. Najčešće imaju ulazni, skriveni i izlazni sloj.
- Učenje - Neuronske mreže uče iz podataka, automatski otkrivajući obrasce i karakteristike, dok se parametri veza između neurona podešavaju tokom procesa učenja.
- Nelinearnost - Sposobnost da modeliraju kompleksne, nelinearne odnose između ulaza i izlaza.
- Paralela s biološkim mozgom - Slično kao biološke neuronske mreže, veze između neurona imaju "snagu" koja se prilagođava tokom učenja.
- Primena - Koriste se za zadatke raspoznavanja uzoraka, predviđanja, klasifikacije i sl. Primenjuju se u raznim domenama kao što su obrada prirodnog jezika, robotika, itd.
- Neuronske mreže predstavljaju moćan alat mašinskog učenja kojim može spoznati i modelirati kompleksne odnose među podacima. Intenzivno se istražuju i imaju široku primenu u savremenoj informatici i tehnologiji.

Primena neuronskih mreža u finansijskom sektoru ima veliki značaj od kojih su najvažnije:

Otkrivanje prevare: Neuralne mreže mogu analizirati velike količine podataka o transakcijama kako bi identifikovale obrasce lažnih aktivnosti, kao što su neobično ponašanje u potrošnji ili sumnjive transakcije. Ovo pomaže finansiskim institucijama da efikasnije otkriju i spreče prevare.

Procena kreditnog rizika: Neuronske mreže mogu analizirati kreditnu istoriju, prihode i druge finansijske podatke kako bi procenile kreditnu sposobnost podnosilaca zahteva za kredit. Ovo omogućava finansijskim institucijama da donose preciznije kreditne odluke zasnovane na dobijenim podacima.

Modeliranje ponašanja kupaca: Neuronske mreže se mogu koristiti za analizu podataka o klijentima, kao što su istorije transakcija i obrasci pregledanja, da bi se bolje razumelo ponašanje i preferencije kupaca. Ovo pomaže finansijskim institucijama da svoje proizvode i usluge prilagode potrebama klijenata.

Osiguranje zajma: Neuronske mreže se mogu koristiti za automatizaciju i pojednostavljenje procesa preuzimanja kredita analizom informacija o podnosiocima zahteva i donošenjem preciznijih odluka o odobravanju kredita.

Predviđanje cene akcija: Neuronske mreže se mogu obučiti na istorijskim podacima o akcijama kako bi pokušale da predvide buduća kretanja cena akcija, što može biti korisno za strategije ulaganja i trgovanja.

Čet-botovi i virtuelni pomoćnici: Finansijske institucije koriste čet-botove i virtuelne asistente na neuronskim mrežama za pružanje personalizovane korisničke usluge i podrške, odgovaranje na pitanja i pomoć u zadacima.

Ključne prednosti korišćenja neuronskih mreža u bankarstvu uključuju poboljšanu tačnost, brzinu i skalabilnost u oblastima kao što su procena rizika, otkrivanje prevara i uvid u klijente. Ovo pomaže poveriocima da donesu bolje odluke i pruže bolju uslugu svojim klijentima.

U prethodnim godinama neuronske mreže su intezivno razmatrane kao alternative statističkim modelima.

Snaga i slabost neuronskih mreža može se sumarno prikazati kao (Abrahams et al., 2024):

- Neuronske mreže lako modeliraju visokosložene, nelinearne odnose između inputa i outputa;
- One su oslobođene bilo kakvih pretpostavki o distribuciji;
- Ovi modeli mogu biti brzo adaptirani na nove informacione inpute (u zavisnosti od algoritma treninga ili obuke);
- Nema formalnih procedura koje bi odredile optimum i vrstu mreže za povezivanje slojeva i čvorova koji povezuju ulazne i izlazne promenljive;
- Neuronske mreže su crne kutije pošto su vrlo teške za interpretaciju; i
- Izračunavanje verovatnoće difolta je moguće samo do određenih granica uz znatan dodatni napor.

Neuronske mreže su delimično podesne u slučaju kada ne postoje očekivanja (zasnovana na iskustvu ili na teoretskim argumentima).

Analiza internog kreditnog rejtinga i procena efekata uvođenja Bazelskih standarda

Bazel standardi su delo Bazelskog skupa za bankarsku kontrolu, osnovani sa težištem da se prema unapred utrđenim pravilima proceni stepen rizika i to kreditnog, koji se nalazi u bankarskom kreditnom portfoliju odnosno njenoj aktivi. Ovi standardi ističu identifikaciju kreditnog portfolija određenih bankarskih klijenata, a zasnovani su isključivo na prihodima ostrarenim po osnovu prodaje (BCBS, 2006). Veliki broja bankarskih institucija je već prihvatio i primenio ovakavu vrstu identifikacije bankarskih klijenata, a isključivo za potrebe projektovanja kreditnog rizika. Utvrđivanje stepena rizika propisanog RW formulama Bazelskih standarda, čini završnu aktivnost u internoj proceni rejtinga i to kreditnog. Sličan vid procene i prognoze efekata primene Bazelskih standarda ističe se i u radu (Altman & Sabato, 2007), u kojem su prognozirani Bazelski standardi primenjeni za preduzeća u Americi.

Rezultati istraživanja su zaključili da se korišćenjem Bazel standarda i njegovih usavršenih i modernizovanih pravila smanjuju kapitalni zahtev prema kreditnim rizicima (Danielsson et al., 2021). Takođe bitno je istaknuti, da nema razlike u formulama Bazelskih pristupa I, II i III za deo preduzeća, a priliom utvrđivanja pondera rizika koji se primenjuju kod analize i vrednovanja kreditnog rizika.

Tabela 1. Bazel parametri i ponderi rizika za segment malih preduzeća, na osnovu uspostavljenog internog kreditnog rejtinga

					Kratkoročni kredit (ef. ročnost M=1)		Srednjoročni kredit (ef. ročnost M=2.5)		Dugoročni kredit (ef. ročnost M=5	
Rejting	PD	LGD	b	R	RW Std. pristup	RW Napredni pristup	RW Std. pristup	RW Napredni pristup	RW Std. pristup	RW Napredni pristup
AAA	0,31%	46,00%	0,20	0,1819	100%	32,65%	100%	45,88%	100%	68,94%
AA	1,14%	46,00%	0,15	0,1469	100%	63,37%	100%	79,27%	100%	105,77%
A	2,92%	46,00%	0,11	0,1047	100%	88,50%	100%	103,49%	100%	128,27%
BBB	7,02%	46,00%	0,09	0,0839	100%	117,50%	100%	131,61%	100%	145,05%
BB	13,18%	46,00%	0,07	0,0804	100%	156,86%	100%	170,62%	100%	193,54%
B	23,03%	46,00%	0,05	0,0802	100%	185,38%	100%	207,48%	100%	227,81%
CCC	50,57%	46,00%	0,03	0,0802	100%	185,88%	100%	192,75%	100%	204,34%

Izvor: Prilagođeno prema Altman & Sabato, 2007

U Tabeli 1. prikazani su po definisanim rejting klasama sledeći pokazatelji rizika: PD (verovatnoća difolta), LGD (Gubitak pri difoltu *Loss Given Default*), b (faktor ročnog prilagođavanja koji odražava uticaj PD) i R (predstavlja korelaciju za izloženosti prema privrednim društvima), koji se smatraju bitnim faktorima u definisanim formulama (Hunt et al., 2020). Na osnovu ovih pokazatelja, za privredna društva manje veličine (gde ukupni godišnji prihod od prodaje iznosi 5 miliona EUR) formulisan je ponder rizika RW, koji odgovara savremenom konceptu Bazel-a. Pored toga, formulisan je i tradicionalan pristup i njemu određeni ponder rizika. Razlika u određivanju RW (ponder kreditnog rizika) postoji samo kod preduzeća velike veličine. Analizira pondera rizika po klasama intenog kreditnog rejtinga je prikazana i za različite ročnosti kredita. U propisanim formulama Bazela, ročnost je prikazana na osnovu pokazatelja efektivne ročnosti M, koji ima vrednost od 1 do 5. Za kredite u kratkom, srednjem i dugom roku prikazane su i određene referentne vrednosti ovog pokazatelja. Interesantno je zapaziti, da se stepen pondera rizika RW povećava, pri porastu ročnosti plasmana. Tako je na primer

RWBBB, M (1) = 117,50% > RWBBB, M (5) = 145,05%, odnosno ponder rizika se povećava sa porastom ročnosti uzimajući PD vrednost za nepromenjenu veličinu. Takođe, interesantno je i zapaziti i situacije kada lošija rejting kategorija, sa većim procenjenim PD parametrom, ima manji RW. Ova situacija se događa kada vrednost PD dostigne tzv. tačku kontaminacije (eng. contamination point). Tako, na primer RWB > RWCCC, gde je RWB = 185,38%, a PDB = 23,03%, dok je RWCCC = 185,88%, a PDCCC = 50,57%. Obrazloženo tumačenje za takvu situaciju stoji u oblazloženju da se za rejting klase koje dostignu tačku sistematizacije PD, ukupni kreditni gubitak većim delom formuliše iz očekivanog gubitka (EL), što dovodi do smanjenja neočekivanog gubitka (UL) koji neposredno zavisi od procenjenog RW tj. pondera rizika (Genest & Brie, 2013). Drugim rečima, nastupa promena u strukturi ukupnog gubitka i to prelivanjem neočekivanog u očekivani gubitak.

Tabela 2. Bazel parametri i ponderi rizika za segment srednjih preduzeća, na osnovu uspostavljenog internog kreditnog rejtinga

					Kratkoročni kredit (ef. ročnost M=1)		Srednjoročni kredit (ef. ročnost M=2.5)		Dugoročni kredit (ef. ročnost M=5	
Rejting	PD	LGD	b	R	RW Std. pristup	RW Napredni pristup	RW Std. pristup	RW Napredni pristup	RW Std. pristup	RW Napredni pristup
AAA	0,31%	46,00%	0,20	0,1999	100%	36,57%	100%	51,34%	100%	76,14%
AA	1,14%	46,00%	0,15	0,1523	100%	71,22%	100%	89,09%	100%	118,90%
A	2,92%	46,00%	0,11	0,1187	100%	101,16%	100%	118,16%	100%	146,50%
BBB	7,02%	46,00%	0,09	0,0998	100%	135,48%	100%	151,67%	100%	178,67%
BB	13,18%	46,00%	0,07	0,0974	100%	168,74%	100%	194,40%	100%	220,59%
B	23,03%	46,00%	0,05	0,0972	100%	218,31%	100%	231,89%	100%	254,37%
CCC	50,57%	46,00%	0,03	0,0967	100%	201,08%	100%	208,89%	100%	221,18%

Izvor: Prilagođeno prema Altman & Sabato, 2007

U Tabeli 2. Iskazani su prema unapred definisanim rejting klasama sledeći pokazatelji: PD, LGD, b i R parametri rizika, koji su definisani kao bitni fakotri propisanih formula, ali za privredna društva srednje veličine (ukupni godišnji prihod od prodaje jednak 25 miliona EUR). Formulisani su i iskazani, ponderi rizika RW, koji odgovaraju savremenom konceptu Bazel pristupa. Ako se izvrši upoređivanje podataka prikazanih u Tabelama 1. i 2., može se utvrditi da su ponderi rizika veći za privredna društva srednje veličine i to po svim rejting klasama i ročnostima. Objašnjenje za ovo može se naći u koloni R, koja definiše regulatorno određene korelacije, koje su zavisne od veličine privrednih društava. Stepen korelacije R, je obrnuto srazmeran stepenu diverzifikacije porftfolija (Crook, Edelman, & Thomas, 2007). Drugačije rečeno, difolt privrednog društva manje veličine u manjoj meri povlači difolte drugih privrednih društava, dok sa rastom njihove veličine ova međuzavisnost raste. Tabela 3. kao i Tabela 1. i 2. iskazuje parametre rizika i pondere rizika RW, za privredna društva velikih veličine (ukupni godišnji prihod od prodaje jednak 50 miliona EUR). Ponderi i parametri rizika, odgovaraju savremenom konceptu Bazel-a.

Tabela 3. Bazel parametri i ponderi rizika za segment velikih preduzeća, na osnovu uspostavljenog internog kreditnog rejtinga

					Kratkoročni kredit (ef. ročnost M=1)		Srednjoročni kredit (ef. ročnost M=2.5)		Dugoročni kredit (ef. ročnost M=5	
Rejting	PD	LGD	b	R	RW Std. pristup	RW Napredni pristup	RW Std. pristup	RW Napredni pristup	RW Std. pristup	RW Napredni pristup
AAA	0,31%	46,00%	0,20	0,2219	100%	41,68%	100%	58,45%	100%	86,40%
AA	1,14%	46,00%	0,15	0,1867	100%	81,31%	100%	101,64%	100%	135,51%
A	2,92%	46,00%	0,11	0,1394	100%	117,02%	100%	136,66%	100%	169,40%
BBB	7,02%	46,00%	0,09	0,1195	100%	157,21%	100%	176,12%	100%	207,24%
BB	13,18%	46,00%	0,07	0,1187	100%	204,41%	100%	222,30%	100%	252,13%
B	23,03%	46,00%	0,05	0,1155	100%	244,06%	100%	259,15%	100%	284,30%
CCC	50,57%	46,00%	0,03	0,1155	100%	216,74%	100%	224,87%	100%	238,41%

Izvor: Prilagođeno prema Altman & Sabato, 2007

Ako se izvrši upoređivanje podataka iskazanih u Tabelama 1., 2. i 3., može se utvrditi da su ponderi rizika, po svim rejting klasama i ročnostima, najveći kod privrednih društava velikih veličina. To utiče na pokazatelj RW, a zbog uvećanja koeficijenata korelacija. U Tabeli 3. pokazatelj RW ima najviše vrednosti po svim rejting kategorijama i ročnostima, za razliku od Tabele 1 i 2. Objašnjenje za opravdani prelazak na napredne koncepte za upravljanje rizikom, može se naći u zaključku sprovedene analize, da se umanjenje kapitalnih zahteva za kreditni rizik kod kredita u kratkom roku očekuje samo za prve tri najbolje rejting klase, što čini oko 52% ukupnog broja korisnika. Uzimajući u obzir da je u Tabeli 1, samo za ove pokazatelje naprednog pristupa RW niži za razliku od pokazatelja standardnog pristupa, moguće je samo za ove rejting klase postići uštedu tj. umanjenje kapitalnih zahteva. Kod kredita na srednjem i dugom roku u Tabeli 2. i 3. umanjenje kapitalnih zahteva za kreditni rizik se predviđa samo kod prve dve klase internog kreditnog rejtinga, što čini 30% ukupnog broja korisnika. U poređenju sa sprovedenim istraživanjem (Altman & Sabato, 2007), koji ističu da prognozirani efekti savremenog koncepta za merenje kreditnog rizika primenom standarda Bazel II dovode do smanjenja zahteva kapitalnih za kreditni rizik, ali na podacima američkih privrednih društava, u ovom radu je utvrđeno da bi efekat smanjenja zahteva kapitalnih postojao samo kod najboljih rejting klasa, u zavisnosti od ročnosti kreditnog plasmana, što čini 32% - 50% privrednih društava. S druge strane, kod svih drugih rejting klasa došlo bi do uvećanja zahteva kapitalnih za kreditni rizik u odnosu na tradicionalni koncept. Zato je na bankarskim institucijama u Srbiji da procene moguće efekte napredovanja i usavršavanja savremenog koncepta, a u pogledu korisnosti i mogućih troškova.

Zaključak

Metode, merenje i procena rizika unutar finansijskih institucija u poslednjoj deceniji su značajno unapređeni, što je uzrokovalo bolje predviđanje uspešnog poslovanja i smanjenje rizika, koji bi uzrokovali nemogućnost dužnika da svoje obaveze prema poveriocima ne mogu izvršavati blagovremeno ili ih uopšte ne mogu realizovati.

Nadalje, za neke klase izloženosti, Bazelski Komitet predlaže osnovnu metodologiju kojom finansijske institucije, kao ulaznu veličinu, uzimaju sopstvenu procenu rizika neplaćanja dužnika, a procene dodatnog faktora rizika su izvedene kroz primenu standardizovonih pravila supervizora.

Osnovna metodologija je dostupna za one finansijske institucije koje mogu da uvere supervizore da su sposobne da odgovore na specfične minimalne zahteve bankarskih sistema unutrašnjeg rejtinga, procesa upravljanja rizika i mogućnosti procene neophodnih komponenti rizika.

Aspekt pristupa zasnovan na internom rangiranju može biti realizovan na više načina. Prvo, tokom perioda i na nivou industrije, Bazelski Komitet očekuje da se sve više finansijskih institucija pomeraju od standardizovanog pristupa ka IRB pristupu i očekivanjima da će one to učiniti kada budu imale potrebne sisteme. Drugo, unutar IRB pristupa. od finansijskih institucija će se očekivati da se kreću od korišćenja osnovnog ka više naprednim metodologijama u skladu sa obogaćivanjem njihove prakse u upravljanju rizicima.

Pojedine finansijske intitucije su sposobne (ili će to postati) da sprovedu pogodnu i doslednu procenu dodatnih komponenti rizika, dok će drugima trebati više vremena da se prestruktuiraju na ovu vrstu procena. Ove dodatne komponente su gubici koji će nastati u slučaju neplaćanja dužnika, nivoa izloženosti dužnika u momentu neplaćanja, efekata garancija i rizika izloženosti kreditnih derivata. \

lstovremeno sa osnovnom metodologijom ustanovljene su i napredne metodologije koje omogućavaju da se koriste sopstvene unutrašnje procene komponenti rizika. Široko korišćenje takvih procena je jedan važan deo dinamičkog i risk-senzitivnog IRB pristupa na takav način da mogu da se prepoznaju i razlikuju one finansijske institucije koje su u mogućnosti da sprovedu dovoljno validnu i kvantifikovanu procenu rizika od onih koje to nisu u stanju.

Možemo zaključiti da validacija od strane finansijskih institucija uključuje dve ključne komponente-validaciju rejting sistema i procenu komponenti rizika i validaciju rejting procesa usmerenih na implementaciju rejtinga sistema. Validacija rejting sistema može nadalje biti razložena na dve komponente: evaluacija izrade rejting sistema ili izrade modela i procene komponenti rizika.

Finansijske institucije su u obavezi da poseduju sofisticirani sistem procene tačnosti i konzistentnosti rejting sistema, procesa, i interno pracene faktora rizika. Istorijski vremenski okviri za podatke koji se koriste u proceni stepena korelacije podataka treba da budu što je moguće duži i u idealnom slučaju da pokriju kompletan poslovni ciklus. Takođe ove institucije moraju do imaju na raspolaganju jasne stres testing procese koje koriste u proceni kapitalne adekvatnosti.

Testiranje mora da sadrži identifikaciju budućih promena ekonomskih uslova i mogućih događaja koji bi mogli nepovoljno uticati na procene difolta (neispunjenje obaveze dužnika) pa samim tim i na ukupni nivo kapitalne adekvatnosti. Testiranje na uslove stresa se mora sprovesti barem jednom u šest meseci. Rezultat testiranja periodično treba da se dostavi kroz izveštaj seniorskom menadžmentu banke.

Za procenu verovatnoće neplaćanja eksterni rejting podaci i interne procene verovatnoće neplaćanja, definicija difolt događaja i rezultirajuća definicija difolt rate (procena neplaćanja) moraju biti slične.

U ovom radu predstavljena je validacija internog kreditnog rejtinga, korišćenjem dostupnih analiza i tumačenja iz dostupne akademske literature. Rezultat sprovednog istraživanja, utvrdio je da je razvijeni interni kreditni rejting za sva privredna društva prošao sve preporuke validnosti i pravilnosti i da je u skladu sa stadardima Bazel koncepta. Takođe, on može da se koristi kao prvi korak kod interne procene potrebnog nivoa kapitala i pokrića mogućih očekivanih i neočekivanih gubitaka. Zato su u radu izračunati ponderi rizika (eng. risk weights - RW) koji se primenjuju kod vrednovanja rizičnosti plasmana na nivou bankarskog portfolija. Na kraju se može istaknuti da se sprovedena metodologija može primeniti na sve bankarske institucije koje posluju u Srbiji i Evropi.

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SIGNIFICANCE OF APPLICATION OF STATISTICAL MODELS IN THE DEVELOPMENT OF THE RATING SYSTEM OF FINANCIAL INSTITUTIONS

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Abstract

The most important system for managing risks and measuring financial performance is the rating system. The rating system is considered an integral part of banks' current operations and their risk management culture. All banks try to highlight its affiliation with current affairs, in order to show the supervisors the necessity of its use for the purpose of determining the minimum regulatory capital requirements.

The Committee in Basel for certain classes of exposure to risks recommends the use of a basic methodology where banking institutions use their own assessment of the risk of non-payment of debtors as an input, while assessments of additional risk factors are applied through the supervisor's standardized rules.

This basic methodology is available for banking institutions that have the ability to satisfy their supervisors that they are capable of meeting certain minimum requirements of the banking system, the risk management process and the ability to assess its essential components.

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In addition to the basic methodology, advanced methodologies have also been defined that provide the possibility of internal assessment of risk components. Wide application of the aforementioned assessments is an important part of the dynamic and risk-sensitive IRB approach (Internal Rating Based). Thus, those banking institutions that have the ability to carry out a certain valid and quantified risk assessment can be identified and distinguished.

Some specific models, procedures and processes of assessing the probability of non-payment in certain situations, through the obtained results, enable the management of banking institutions to analyze in detail the real picture of possible debtors, which ultimately provides a possible better analysis of their default.

Keywords: *default probability, debtor, models, internal rating, statistical analysis, adequacy of bank capital.*

JEL: C26, G21

Introduction

The basic basis for determining the risk exposure rating or the rating of other contracting parties at a smaller number of banking institutions, and within certain portfolios, was the procedure of the probability of fulfillment of obligations or other quantitative tools.

Such procedures should have the possibility to be developed by the supplier (vendor) and mostly in addition to qualitative and quantitative factors (financial ratios), contain standardized factors (payment history, credit reports, etc.). (Bessis J, 2019)

Such tools were applied by a small number of banking institutions with large corporate exposure, while a few of them used these tools in situations of the middle market or users from small businesses. The use of credit score models ("scorecard" categories, models of defaults, vendors and consultants) can be cited as an example of the above situation.

Also, the mentioned models contain essential elements in risk assessment procedures in a large number of institutions. When constructing banks, financial dependent variables are first defined, which appear when providing information on the percentage of probability of default.

Through the sample of the considered loan, and by applying the available historical data, the banking institution evaluates the influence of each of these dependent variables on the default procedure. The established assessment coefficients are further used on the data of current loans and appear as a result that is determined in the assessment of the issue of percentage probability of default. The result is then converted into a rating degree (the real inputs in such models are very identical to the quantitative elements of risk, determined by the appraiser).

Activities and processes based on statistical models play a more important role in smaller corporate loans than in mid-sized markets or large corporations.

Some banking institutions have based their ratings exclusively on statistical default and credit score models or special objectives of financial analysis, without taking into account simple mechanical processes. Tactic ratings allow the assignment of ratings to adjust the rating to a certain pre-limited degree based on assessment factors. (Brealey R., 2021)

In a certain situation of a defined process, the scorecard defines the degree, while the evaluator, based on personal analysis, can define the final degree downward or upward, by a maximum of one or two degrees.

In addition, quantitative and assessment factors can be assigned maximum points, effectively limiting the impact of consideration of a particular assessment on the final rating. Almost 20% of banking institutions apply this concept in their large corporations, while an identical percentage of institutions declared that they apply this concept to their smaller corporations and mid-markets. Putting limits on the assessment is more professional when these assessments are exclusively applied to the growth of the rating, not to its decline. The largest number of institutions assign ratings by applying the most significant parts of the assessment, where the relative importance is indicated by the parts that are not limited.

Regression analysis

In statistical modeling, regression analysis is a process of statistical analysis based on which the mutual relationship between the dependent or criterion variable and independent (predicator) variables is evaluated. (Matz L., 2017)

The results obtained on the basis of the regression analysis point out that the value data of the dependent variable changes with the change of the value data of some independent variable, while the other value data of the independent variables remain unchanged.

Approximation of the regression function appears as a permanent task of regression analysis, which highlights the connection between dependent and independent variables. This analysis is also used to evaluate the functional dependence between the mentioned variables, as well as the nature of those dependencies.

In practice, for example, we may be interested in the dependence between employees' earnings and their education, interest rates and money supply. In order to determine whether there is a dependence between certain phenomena and to what extent their dependence is, it is necessary to apply a specific regression model.

Regression analysis is used for two totally different purposes. First of all, it is applied for planning, forecasting and possible prediction, in situations where its use is identified with the field of machine learning. It is then used in situations to determine cause-and-effect relationships between dependent and independent variables.

In order to successfully use this type of predictive analysis, the researcher should carefully define and explain the existence of a cause-and-effect relationship between the variables, that is, their functional relationship. A functional relationship is particularly important in situations where researchers believe that only data from a sample or statistical set and the appropriate functional relationship will be used to assess a cause-and-effect relationship.

Regression analysis in financial institutions

A key advantage of regression models in financial institutions is their ability to analyze complex relationships between variables and provide quantitative estimates that support informed business decision making. (Gitman L., 2019)

Input characteristics that are not relevant to the model can seriously impair the quality and stability of the model when used to predict the credit risk associated with this data. It is preferable that the variables, which do not have a great influence on the results of the model, are simply ignored and thereby simplify the model, which in any case makes the work easier for persons performing regression analysis.

The way to deal with this problem is to divide the cause into two parts, where one part (the training sample) is used to evaluate the model and the other part is the hold-out sample (the rest of the sample) which is used in the validation of the results.

The consistency of the results of both samples are simultaneously taken as indicators of model stability.

In financial institutions, regression analysis is most often used in the following cases:

a) Credit analysis: Regression models are used to assess the credit risk of clients. Models such as logistic regression are used to predict the likelihood that a customer will repay the loan regularly.
b) Asset and liability management: Financial institutions use regression models to predict deposit and loan levels, which helps them manage their balance sheet and liquidity risks.
c) Marketing strategies: Regression analysis is used to identify the most profitable customer segments and determine the most effective marketing channels and campaigns.
d) Fraud prevention: Regression models are used to detect suspicious transactions and behavior patterns that may indicate fraud.
e) Price adjustment: Banks use regression models to determine optimal interest rates and fees based on market conditions and the risk profile of clients.

f) Risk management: Regression models are used to assess the credit, market and operational risk to which the bank is exposed.

Discriminant analysis

The discriminant analysis is performed in a similar way as in the linear regression model.

In fact, the proportions between the coefficients of the regression model are equal to the corresponding proportions of the discriminant analysis. The difference between these two methods is theoretical: while in the regression model, the characteristics have a deterministic nature, and the default state is a random variable. With determinant analysis, it is quite the opposite, ie. characteristics represent a random variable while the default state is deterministic. These differences are virtually unimportant in practice.

We can conclude that the advantages and disadvantages of discriminant analysis using this model are similar to those of the regression model, namely:

- Discriminant analysis is a widely known method with estimation algorithms available;
- Once the coefficients are estimated, the results can be calculated directly as linear functions;
- Since the characteristics Xi are realized on the basis of random variables, then the statistical tests of the significance of the model and coefficients are based on the assumptions of multivariate normality. This is however unrealistic for variables typically used in rating models, such as balance sheet financial ratios. Therefore, the methods of analyzing model stability and the possibilities of coefficients are limited in the comparison between the sample and the rest of the sample; and
- Absolute values of the discriminant function cannot be interpreted by levels.

One possible way of obtaining homoscedastic quantities is the calculation of estimated quantities through the weighted least squares (WLS) method. Although this is possible, it is not a common practice because, in order to obtain the frequency of defaults, the data must be grouped before performing the estimation. (Greuning H., 2018)

Clustering involves significant practical problems such as determining the size and number of groups and how to treat different covariates within a single group (Zhou et al., 2024).

Logit and Probit models represent a better way of estimation because they do not require prior grouping as in the ML method (it is a maximum likelihood method). For binomially dependent variables, the probability function reads:

$$\mathbf{L(b)} = P(\boldsymbol{b'} \times \mathbf{X_i})^{yi} \times \mathbf{(1\text{-}P(\boldsymbol{b'} \times X_i)^{1\text{-}yi})} \qquad \mathbf{(1)}$$

In the probit model, the function P represents the function of the normal probability distribution, and in the Logit model, it represents the logarithmic function of the probability distribution. Through this equation, the estimation of the model is theoretically convincing and easy to handle. (Samuels J., 2016)

Furthermore, this ML approach leads us to a wide set of tests to evaluate the model and its variables. Usually, the choice of link function is not based on a theoretical basis. Users who are closer to using the normal probability distribution will opt for the Probit model.

And really, the differences in results for both classes of models are often negligible. This is because both functions have similar shapes except for the tails, which are more difficult to account for in the Logit model. It is true that the Logit model is easier to handle because it is easier to calculate the estimator.

However, the complexity of calculations today is often insignificant, since the largest number of users use statistical software packages where estimation algorithms are integrated into software solutions. The fact that the coefficients of the Logit model can be interpreted more easily is also important (Ochuba et al., 2024).

To understand this, we will transform the Logit model given by equation (1) as follows:

$$P_i/(1-P_i) = e^{\beta} \times X_i \qquad (2)$$

On the left side of equation (2) there are relations between the probability of default and the probability of survival (survival).

Now it can be easily seen that the variation of one variable x_i by one unit has an effect equal to e^{β} on the probability when the quantity β_k coefficient of the variable x_i.

The transformed coefficient e^{β} is called the adds-ratio. It represents the multiplied effect of borrower characteristics on probability. Therefore, in the Logit model, the coefficient can be interpreted in a probable way, which is not the case in the Probit model.

Panel models

The methods described so far are cross-sectional methods because all variables refer to the same time period. Financial institutions typically spread sets of variables over more than one period with each borrower. In this case, it is possible to extend cross-sectional data inputs to panel data sets. 42

In this way, we increase the number of observations available to the appraiser and also increase the stability and precision of the rating model. Panel models can also integrate macroeconomic variables.

Macroeconomic variables can improve the model for several reasons. First, many sources of macroeconomic data are more up-to-date and more accessible than meso and micro data, because data on macroeconomic variables are published by official national statistics. For example, financial ratios

[42] In statistics and econometrics, the term panel data refers to multidimensional data. They contain observations of multiple phenomena over multiple time periods in the same individual. Time-series or cross-sectional data are special cases of panel data that are unidimensional.

calculated on the basis of balance sheet information are usually updated annually and are no older than two years when we use them for risk assessment. (Dowling E.T., 2017)

Oil prices, for example, are available to us according to the daily data frequency, likewise, the prices of precious metals, the prices of shares on the stock exchanges, and the like change several times during the day, and we can get that information.

Emphasizing macroeconomic inputs in the model can be used to create credit risk stress tests. Since macroeconomic variables primarily affect the absolute values of default probabilities, it is reasonable to incorporate macroeconomic imputations into these classes of models when estimating default probabilities. (Engeimann B., at.all. 2018)

At first glance, panel models are similar to sectional models. In fact, many developers ignore the dynamic pattern of variables and simply plug them into Logit and Probit models. (Alastair L., 2022)

In general, cross-sectional data meet these requirements, but panel data do not meet the same requirements, and this is because observations of the same period and observations of the same debtor may be correlated. Introducing correlation into estimation procedures is complicated. (Mishkin F., 2020)

For example, the fixed effect estimator familiar to us from panel analysis of a continuous dependent variable is not available in the Probit model. In addition, the modified fixed-effect estimator in the Logit model excludes all non-defaulting debtors from the analysis and thus appears to us to be inappropriate. Finally, the random effect estimators prescribed in the literature can only be calculated using specialized software packages.

Hazard models

All the models listed so far have tried to assess the riskiness of the borrower by estimating a certain type or score that would indicate whether or not the borrower is prone to default within a specific forecast horizon.

However, no exact prediction of default in time has been made. In addition, such approaches do not allow the evaluation of the debtor's risk in the future, which would not enter into default during a reference period of time.

These shortcomings can be overcome by using a hazard model, which explicitly treats the survival function and consequently the time at which we consider debt default.

Within this class of models, the Cox proportional hazards model is the most common regression model since it is not based on any assumptions regarding the nature or shape of the underlying survival distribution.

The model estimates that the underlying hazard rate (rather than survival time) is a function of the independent variable. No assumption is made about the nature or form of the hazard function. Therefore, the Cox regression model is actually a semiparametric model.

It can be described as: $h_i(t/x_i) = h_0(t) \times e^{\beta \times \mathbf{xi}}$ **(3)**, where the quantity $h_i(t/x_i)$ indicates the resulting hazard given by the covariates of the respective debtor in the respective survival period t.

The expression h0(t) is called the hazard baseline and represents the hazard when all independent variables are equal to zero. If the covariates are measured as deviations in relation to their respective mean values, then the quantity h0(t) can be interpreted as the hazard rate for some average borrower. The model presented above contains important assumptions. First, he specifies a multiple relationship between the hazard function and the logarithmic linear function of the dependent variable, which indicates that the hazard ratio for two debtors does not depend on time, ie. that the relative riskiness of the debtor is constant, hence the name for the Cox proportional hazard model.

In this model, the default point in time is assumed to be a continuous random variable. However, it often happens that the debtor's financial conditions are not viewed continuously (continuously) but as discrete values in time. Furthermore, covariates are treated as constant over time while typical dependent variables such as, for example, financial relationships change over time.

Although there are some more advanced models that contain the above-mentioned features, the evaluation in such models becomes complex.

The advantages and disadvantages of the hazard model can be summarized as (Alirezaie et al., 2024):

- Hazard models enable estimation of the survival function for all borrowers. The time period of historical data on default is the basis for assessing the debtor's survival and the probability of default in the following time period and
- These models indirectly estimate realistic assumptions about default in the future time period.

Neural networks

Neural networks are a type of computer system inspired by the structure and functions of biological neural networks in the brain. The main components of neural networks are (Abrahams et al., 2024a):

- Network architecture - Consists of interconnected "nodes" or "neurons" that process information. Most often they have an input, hidden and output layer.
- Learning - Neural networks learn from data, automatically discovering patterns and features, while the parameters of connections between neurons are adjusted during the learning process.
- Nonlinearity - Ability to model complex, non-linear relationships between inputs and outputs.
- Parallel to the biological brain - Similar to biological neural networks, the connections between neurons have a "strength" that adjusts during learning.
- Application - They are used for the tasks of pattern recognition, prediction, classification, etc. They are applied in various domains such as natural language processing, robotics, etc.
- Neural networks are a powerful machine learning tool that can recognize and model complex relationships between data. They are intensively researched and widely used in modern IT and technology.

The application of neural networks in the financial sector is of great importance, the most important of which are:

Fraud detection: Neural networks can analyze large amounts of transaction data to identify patterns of fraudulent activity, such as unusual spending behavior or suspicious transactions. This helps financial institutions detect and prevent fraud more effectively.

Credit risk assessment: Neural networks can analyze credit history, income and other financial data to assess the creditworthiness of loan applicants. This allows financial institutions to make more accurate credit decisions based on the data obtained.

Modeling customer behavior: Neural networks can be used to analyze customer data, such as transaction histories and browsing patterns, to better understand customer behavior and preferences. This helps financial institutions to tailor their products and services to the needs of their customers.

Loan underwriting: Neural networks can be used to automate and streamline the loan underwriting process by analyzing information about applicants and making more accurate loan approval decisions.

Stock price prediction: Neural networks can be trained on historical stock data to try to predict future stock price movements, which can be useful for investment and trading strategies.

Chatbots and virtual assistants: Financial institutions use neural network-based chatbots and virtual assistants to provide personalized customer service and support, answer questions and assist with tasks.

Key benefits of using neural networks in banking include improved accuracy, speed and scalability in areas such as risk assessment, fraud detection and customer insight. This helps creditors make better decisions and provide better service to their customers.

In previous years, neural networks have been intensively discussed as alternatives to statistical models.

The strength and weakness of neural networks can be summarized as (Abrahams et al., 2024):

- Neural networks easily model highly complex, non-linear relationships between input and output;
- They are free from any assumptions about distribution;
- These models can be quickly adapted to new information inputs (depending on the training or training algorithm);
- There are no formal procedures that would determine the optimum and type of network for connecting layers and nodes that connect input and output variables;
- Neural networks are black boxes because they are very difficult to interpret; and
- Calculating the probability of default is only possible up to certain limits with considerable additional effort.

Neural networks are partially suitable in the case where there are no expectations (based on experience or on theoretical arguments).

Analysis of internal credit rating and assessment of the effects of the introduction of Basel standards

The Basel standards are the work of the Basel Group for Banking Control, established with the aim of assessing the degree of credit risk in the bank's credit portfolio, i.e. its assets, according to pre-established rules. These standards emphasize the identification of the credit portfolio of certain banking clients, and are based solely on revenues obtained from sales (BCBS, 2006). A large number of banking institutions have already accepted and applied this type of identification of banking clients, exclusively for the purposes of projecting credit risk. Determining the degree of risk prescribed by the RW formulas of the Basel standards is the final activity in the internal assessment of the credit rating. A similar type of assessment and forecast of the effects of the implementation of the Basel standards is highlighted in the paper (Altman & Sabato, 2007), in which the Basel standards applied to companies in America are forecast. The results of the research concluded that using the Basel standard and its improved and modernized rules reduce the capital requirement for credit risks (Danielsson et al., 2021). It is also important to point out that there is no difference in the formulas of Basel

Approaches I, II and III for a part of the company, and when determining the risk weights that are applied in the analysis and evaluation of credit risk.

Table 1. Basel parameters and risk weights for the small business segment, based on the established internal credit rating

					Short-term loan (effective maturity M=1)		Medium-term loan (effective maturity M=2.5)		Long-term loan (effective maturity M=5)	
Rating	PD	LGD	b	R	RW Std. access	RW Advanced access	RW Std. access	RW Advanced access	RW Std. access	RW Advanced access
AAA	0,31%	46,00%	0,20	0,1819	100%	32,65%	100%	45,88%	100%	68,94%
AA	1,14%	46,00%	0,15	0,1469	100%	63,37%	100%	79,27%	100%	105,77%
A	2,92%	46,00%	0,11	0,1047	100%	88,50%	100%	103,49%	100%	128,27%
BBB	7,02%	46,00%	0,09	0,0839	100%	117,50%	100%	131,61%	100%	145,05%
BB	13,18%	46,00%	0,07	0,0804	100%	156,86%	100%	170,62%	100%	193,54%
B	23,03%	46,00%	0,05	0,0802	100%	185,38%	100%	207,48%	100%	227,81%
CCC	50,57%	46,00%	0,03	0,0802	100%	185,88%	100%	192,75%	100%	204,34%

Source: Adapted from Altman & Sabato, 2007

Table 1 shows the following risk indicators by defined rating classes: PD (probability of default), LGD (Loss Given Default), b (term adjustment factor that reflects the impact of PD) and R (represents the correlation for exposures to commercial companies), which are considered essential factors in defined formulas (Hunt et al., 2020). Based on these indicators, a risk weight RW was formulated for smaller companies (where the total annual revenue from sales is EUR 5 million), which corresponds to the modern concept of Basel. In addition, a traditional approach was formulated and a risk weight was assigned to it. The difference in determining the RW (credit risk weight) exists only for large-sized companies. It analyzes the risk weights by classes of the internal credit rating and is shown for different loan maturities. In the prescribed Basel formulas, maturity is shown based on the effective maturity indicator M, which has a value from 1 to 5. For loans in the short, medium and long term, certain reference values of this indicator are also shown. It is interesting to note that the level of risk weighting of RW increases with an increase in the maturity of the placement. For example, RWBBB, M (1) = 117.50% > RWBBB, M (5) = 145.05%, that is, the risk weight increases with the increase in maturity, taking the PD value for the unchanged size. Also, it is interesting to note the situations when a worse rating category, with a higher estimated PD parameter, has a lower RW. This situation occurs when the PD value reaches the so-called contamination point (eng. contamination point). So, for example RWB > RWCCC, where RWB = 185.38% and PDB = 23.03%, while RWCCC = 185.88% and PDCCC = 50.57%. The reasoned interpretation for such a situation is based on the reasoning that for rating classes that reach the PD systematization point, the total credit loss is mostly formulated from the expected loss (EL), which leads to a reduction of the unexpected loss (UL) which directly depends on the estimated RW, i.e. risk weighting (Genest & Brie, 2013). In other words, there is a change in the structure of the total loss, and that is by spilling the unexpected into the expected loss.

Table 2. Basel parameters and risk weights for the segment of medium-sized companies, based on the established internal credit rating

					Short-term loan (effective maturity M=1)		Medium-term loan (effective maturity M=2.5)		Long-term loan (effective maturity M=5)	
Rating	PD	LGD	b	R	RW Std. access	RW Advanced access	RW Std. access	RW Advanced access	RW Std. access	RW Advanced access
AAA	0,31%	46,00%	0,20	0,1999	100%	36,57%	100%	51,34%	100%	76,14%
AA	1,14%	46,00%	0,15	0,1523	100%	71,22%	100%	89,09%	100%	118,90%
A	2,92%	46,00%	0,11	0,1187	100%	101,16%	100%	118,16%	100%	146,50%
BBB	7,02%	46,00%	0,09	0,0998	100%	135,48%	100%	151,67%	100%	178,67%
BB	13,18%	46,00%	0,07	0,0974	100%	168,74%	100%	194,40%	100%	220,59%
B	23,03%	46,00%	0,05	0,0972	100%	218,31%	100%	231,89%	100%	254,37%
CCC	50,57%	46,00%	0,03	0,0967	100%	201,08%	100%	208,89%	100%	221,18%

Source: Adapted from Altman & Sabato, 2007

Table 2 shows the following indicators according to predefined rating classes: PD, LGD, b and R risk parameters, which are defined as important factors of prescribed formulas, but for medium-sized companies (total annual sales revenue equal to EUR 25 million). RW risk weights, which correspond to the modern concept of the Basel approach, have been formulated and presented. If the data shown in Tables 1 and 2 are compared, it can be determined that the risk weightings are higher for medium-sized companies in all rating classes and maturities. An explanation for this can be found in column R, which defines regulatory determined correlations, which depend on the size of the companies. The degree of correlation R is inversely proportional to the degree of portfolio diversification (Crook, Edelman, & Thomas, 2007). In other words, the default of a smaller company leads to a smaller extent of the defaults of other companies, while with the growth of their size, this interdependence increases. Table 3, as well as Tables 1 and 2, shows the risk parameters and risk weights of RW, for large-sized companies (total annual sales revenue equal to EUR 50 million). Risk weights and parameters correspond to the modern concept of Basel.

Table 3. Basel parameters and risk weights for the segment of large companies, based on the established internal credit rating

					Short-term loan (effective maturity M=1)		Medium-term loan (effective maturity M=2.5)		Long-term loan (effective maturity M=5)	
Rating	PD	LGD	b	R	RW Std. access	RW Advanced access	RW Std. access	RW Advanced access	RW Std. access	RW Advanced access
AAA	0,31%	46,00%	0,20	0,2219	100%	41,68%	100%	58,45%	100%	86,40%
AA	1,14%	46,00%	0,15	0,1867	100%	81,31%	100%	101,64%	100%	135,51%
A	2,92%	46,00%	0,11	0,1394	100%	117,02%	100%	136,66%	100%	169,40%
BBB	7,02%	46,00%	0,09	0,1195	100%	157,21%	100%	176,12%	100%	207,24%
BB	13,18%	46,00%	0,07	0,1187	100%	204,41%	100%	222,30%	100%	252,13%
B	23,03%	46,00%	0,05	0,1155	100%	244,06%	100%	259,15%	100%	284,30%
CCC	50,57%	46,00%	0,03	0,1155	100%	216,74%	100%	224,87%	100%	238,41%

Source: Adapted from Altman & Sabato, 2007

If the data presented in Tables 1, 2 and 3 are compared, it can be determined that the risk weights, for all rating classes and maturities, are the highest for large companies. This affects the RW indicator, and due to the increase in correlation coefficients. In Table 3, the RW indicator has the highest values for all rating categories and maturities, in contrast to Tables 1 and 2. The explanation for the justified transition to advanced risk management concepts can be found in the conclusion of the conducted analysis, that the reduction of capital requirements for credit in the short term, he expects credit risk only for the first three best rating classes, which makes up about 52% of the total number of users. Taking into account that in Table 1, only for these indicators of the advanced approach, the RW is lower in contrast to the indicators of the standard approach, it is possible only for these rating classes to achieve savings, i.e. reduction of capital requirements. For medium- and long-term loans in Tables 2 and 3, the reduction of capital requirements for credit risk is predicted only for the first two classes of internal credit rating, which makes up 30% of the total number of users. In connection with the conducted research (Altman & Sabato, 2007), which points out that the forecasted effects of the modern concept for measuring credit risk using the Basel II standard lead to a reduction in capital requirements for credit risk, but based on the data of American companies, in this paper it was determined that the effect of reducing capital requirements would exist only in the best rating classes, depending on the maturity of the credit placement, which accounts for 32% - 50% of companies. On the other hand, with all other rating classes, there would be an increase in capital requirements for credit risk compared to the traditional concept. Therefore, it is up to the banking institutions in Serbia to assess the possible effects of advancing and improving the modern concept, in terms of usefulness and possible costs.

Conclusion

The methods, measurement and assessment of risk within financial institutions have been significantly improved in the last decade, which has resulted in better forecasting of successful operations and reduction of risks, which would cause debtors to be unable to fulfill their obligations to creditors in a timely manner or unable to realize them at all.

Furthermore, for some classes of exposure, the Basel Committee proposes a basic methodology by which financial institutions, as an input size, take their own assessment of the risk of non-payment of the debtor, and assessments of the additional risk factor are derived through the application of standardized supervisor rules.

The core methodology is available to those financial institutions that can satisfy supervisors that they are capable of meeting the specific minimum requirements of banking internal rating systems, risk management processes and the ability to assess the necessary risk components.

The aspect of access based on internal ranking can be realized in several ways. First, over the period and at the industry level, the Basel Committee expects more and more financial institutions to move away from the standardized approach to the RBI approach and expects that they will do so once they have the necessary systems in place. Second, within the RBI approach. financial institutions will be expected to move from the use of basic to more advanced methodologies in line with the enrichment of their risk management practices.

Certain financial institutions are capable (or will become) of conducting a convenient and consistent assessment of additional risk components, while others will need more time to restructure to this type of assessment. These additional components are the losses that will occur in case of non-payment by the debtor, the level of exposure of the debtor at the moment of non-payment, the effects of guarantees and the risk of exposure to credit derivatives.

At the same time as the basic methodology, advanced methodologies have been established that allow the use of one's own internal assessments of risk components. The widespread use of such assessments is an important part of a dynamic and risk-sensitive RBI approach in such a way that those financial institutions that are able to conduct a sufficiently valid and quantified risk assessment can be recognized and distinguished from those that are unable to do so.

We can conclude that the validation by financial institutions includes two key components - the validation of the rating system and the assessment of the risk components and the validation of the rating processes aimed at the implementation of the rating system. The validation of the rating system can further be broken down into two components: the evaluation of the development of the rating system or the development of the model and the assessment of the risk components.

Financial institutions are required to have a sophisticated system of assessing the accuracy and consistency of the rating system, process, and internal monitoring of risk factors. Historical time frames for the data used in assessing the degree of data correlation should be as long as possible and ideally cover the entire business cycle. Also, these institutions must have at their disposal clear stress testing processes that they use in assessing capital adequacy.

The testing must contain the identification of future changes in economic conditions and possible events that could adversely affect default assessments (debtor's default) and therefore the overall level of capital adequacy. Stress testing must be conducted at least once every six months. The results of the testing should be submitted periodically through a report to the senior management of the bank.

To assess the probability of default, external rating data and internal estimates of the probability of default, the definition of the default event and the resulting definition of the default rate (estimate of default) must be similar.

This paper presents the validation of the internal credit rating, using available analyzes and interpretations from the available academic literature. As a result of the conducted research, it was established that the developed internal credit rating for all economic companies passed all recommendations of validity and regularity and that it is in accordance with the standards of the Basel concept. Also, it can be used as a first step in an internal assessment of the required level of capital and the coverage of possible expected and unexpected losses. That is why the paper calculated risk weights (eng. risk weights - RW) which are applied when evaluating the riskiness of placements at the level of the banking portfolio. Finally, it can be pointed out that the implemented methodology can be applied to all banking institutions operating in Serbia and Europe.

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