

The Impact of the Dodd-Frank Act on Small Business*

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February 15, 2019

Abstract

There are concerns that the Dodd-Frank Act (DFA) has impeded small business lending. By increasing the fixed regulatory compliance requirements needed to make business loans and operate a bank, the DFA disproportionately reduced the incentives for all banks to make very modest loans and reduced the viability of small banks, whose small-business share of C&I loans is generally much higher than that of larger banks. Despite an economic recovery, the small loan share of C&I loans at large banks and banks with \$300 or more million in assets has fallen plunged 9 percentage points since the DFA was passed in 2010, with the magnitude of the decline twice as large at small banks. Controlling for cyclical effects and bank size, we find that these declines in the small loan share of C&I loans are almost all statistically attributed to the change in regulatory regime. Examining Federal Reserve survey data, we find evidence that the DFA prompted a relative tightening of bank credit standards on C&I loans to small versus large firms, consistent with the DFA inducing a decline in small business lending through loan supply effects. We also empirically model the pace of business formation, finding that it had downshifted during the initial period of the DFA before efforts to provide regulatory relief to smaller banks via modifying implementation rules.

Keywords: small business lending, business formation, regulation, Dodd-Frank, secular stagnation

JEL Codes: E40, E50, G21

* We thank Mark Bils, Iftekhar Hasan, Kose John, Pete Klenow, Monika Piazzesi, Ned Prescott, Martin Schneider, John Taylor, Lena Tonzer, Kevin Warsh, Michael Weiss, and seminar participants at the Stanford Macroeconomics Faculty Lunch, the 2017 26th Annual Rome International Conference on Money, Banking, and Finance, the 2018 Third Entrepreneurial Finance Conference, and Harvard Business School for suggestions. Our study substantially revises an earlier NBER working paper of the same title by Bordo and Duca (2018). We thank Tyler Atkinson, Daniel Chapman, and Valerie Grossman for providing excellent research assistance, as well as Jim Carlson and John Genovese for providing early, excellent IT support. The views expressed are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System. Any remaining errors are those of the authors.

The Dodd Frank Act of 2010 (DFA) was designed to overcome the sources of excessive leverage and systemic risk in the U.S. financial sector perceived to have created the Great Financial Crisis of 2007-2008. Since then considerable controversy has swirled over the efficacy of various components of the multi-faceted Act. Many have been critical of the Volcker Rule, others have praised the elevation of capital ratios and the requirements for banks to undergo periodic stress tests. However, there has been mounting concern in the financial community, the Congress and the press over the negative impact of the DFA regulations on small banks and businesses.

One such concern is that the DFA has unduly impeded small-business lending (Cole, 2012, 2018), thereby slowing the pace of business formation, which has been unusually weak in recent years (e.g., see Decker, et al., 2016 and Figure 1). From Kaufman Foundation data on funding for start-ups in their first year, Cole and Sokolyk (2018) document that 44 percent of start-ups used bank business debt and 55 percent used personal debt. In addition, Doerr (2018) has found that because stress tests for large banks involve scenarios with large house price declines, DFA has by impeding home equity lending by such banks, slowed business formation in counties where entrepreneurs were more reliant for funding by borrowing against their home equity. Through both the C&I (our findings) and home equity line (Doerr's findings) channels, DFA has slowed U.S. business formation. Since DFA is the U.S. manifestation of Basel III, one may expect effects elsewhere. Indeed, business formation also shifted lower in France and Germany after Basel III was announced (see Appendix B and Appendix Table B1).

By increasing the fixed regulatory compliance requirements¹ for making business loans and operating a bank, the DFA has disproportionately reduced the incentives of all banks to make very small C&I loans. It also reduced the viability of lesser-sized banks, whose small business

¹ For example, increased documentation and recorded ratings of each loan, especially at stress-tested banks.

share of commercial and industrial (C&I) loans is generally much higher than that of larger banks (see Dahl et al., 2016; Lux and Greene, 2015, and Reichow, 2017). While DFA added the reporting of loans to minority and women lending specifically for C&I loans to small firms, DFA's impact on the regulatory environment arguably raised reporting and other burdens for making small business loans. For example, C&I loans to small firms relative to others may also decline to the extent that stress tests tend to apply higher risk assessments on loans to small or new firms, consistent with the arguments and evidence in Covas (2017).² Nevertheless, Cortes, et al. (2018) found that the growth of small-sized C&I loan extensions did not differ between large banks that were subject to stress tests between 2012 and 2015. Our preliminary results using extensions data (in process) suggest that this difference in results between Covas (2017) and Cortes, et al. may reflect that much of the impact of DFA on C&I lending seems to have occurred before 2012.

To meet greater regulations, banks have experienced increased expenses and, at smaller banks, reduced profitability. In a study of small bank holding companies (assets under \$5 billion), Cyree found that DFA was associated with statistically significant 3 bp. rise in costs (scaled by assets), .6 percent greater employment per quarter, and an 8 bp. decline in returns on assets, ROA. Consistent with Cyree's qualitative findings, Feldman et al. (2013) earlier note that a Federal Reserve Bank of Kansas City survey indicated that most small banks would add one to two new employees to comply with DFA (near survey results from Pierce et al., 2014), a magnitude which can notably impact expenses and profitability, as Feldman et al. (2013) demonstrate.³ It has been argued that through these intensive and extensive margin effects, the DFA has impeded small

² It is beyond the scope of this study to assess whether new risk assessments are optimal in obtaining benefits from lowering bank failure risk versus incurring indirect costs in the form of negative externalities from lowering competition from—and entry by—small firms whose access to bank credit may have been reduced.

³ They estimate the average impact at 5, 11, and 28 bps. for banks with assets between \$250 and \$500 million, \$50 to 250 million, and under \$50 million, respectively.

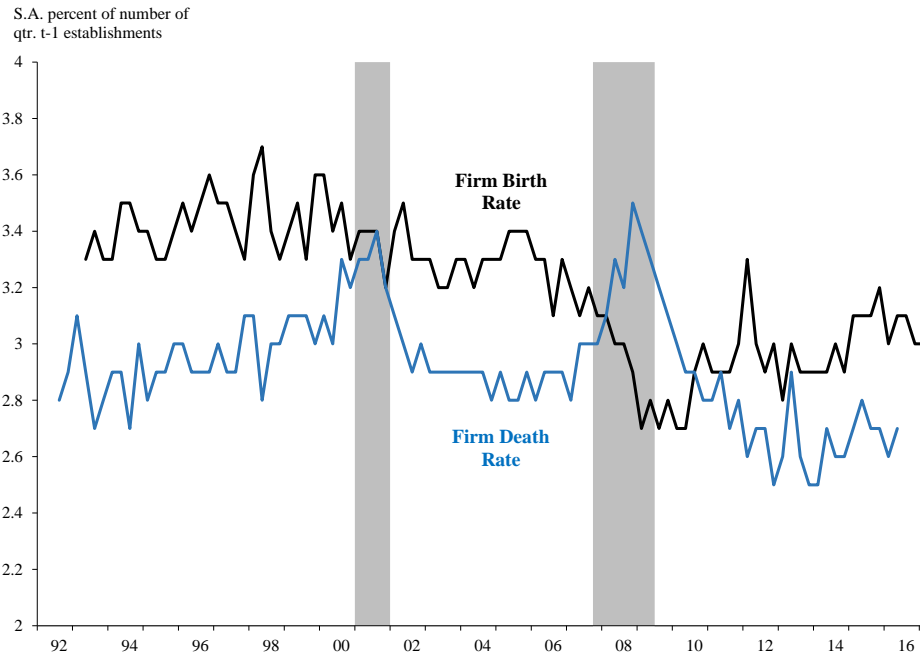
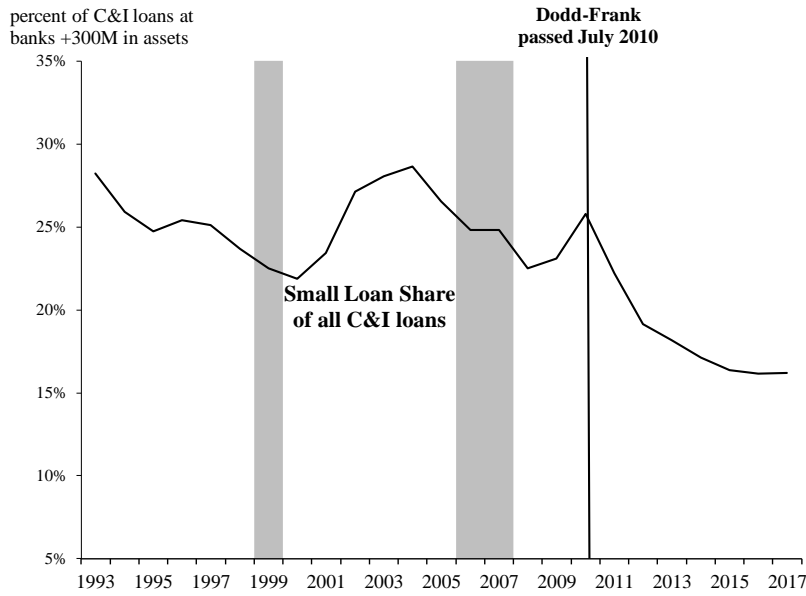


Figure 1: Despite an Economic Recovery, New Business Formation Was Below Its Pre-Recession (2002-07) Pace Until Late 2014. Source: U.S. Bureau of Labor Statistics.

business lending during the recovery from the Great Recession.

Indeed, despite an economic recovery, the share of C&I loans under \$1 million in size at banks with \$300 million or more in assets has plunged since the DFA was passed in 2010 (Figure 2). Driving this development was a decline in 2011 in the real aggregate volume of C&I loans under \$1 million in size and a sluggish and only partial unwinding by 2016. This contrasts with an 82 percent rise in the real aggregate volume of loans over \$1 million in size since 2010. This is not an artifact of inflation or nominal GDP growth that caused a migration of loans between the size categories as formal robustness checks later demonstrate and as illustrated in Figure 3 by a sharp break in the relative trends in the two series since 2010. Indeed, between 1993 and 2010, the small and large size real loan series trended together and rose by roughly similar amounts: 79 and 67 percent, respectively.

These patterns also occurred at large banks, where the small loan share of C&I loans



Sources: Consolidated Reports of Condition and Income, Federal Financial Institutions Examination Council, and authors' calculations. Shares at banks with assets of at least \$300 million—consistently available from 1993-2016. Shaded areas are recessions.

Figure 2: The Small Loan Share of C&I loans After the Dodd-Frank Act Passes

Sources: Consolidated Reports of Condition and Income, Federal Financial Institutions Examination Council, and authors' calculations. Shares at banks with assets of at least \$300 million (\$2004 using the CPI)—consistently available from 1993-2016. Shaded areas are recessions.

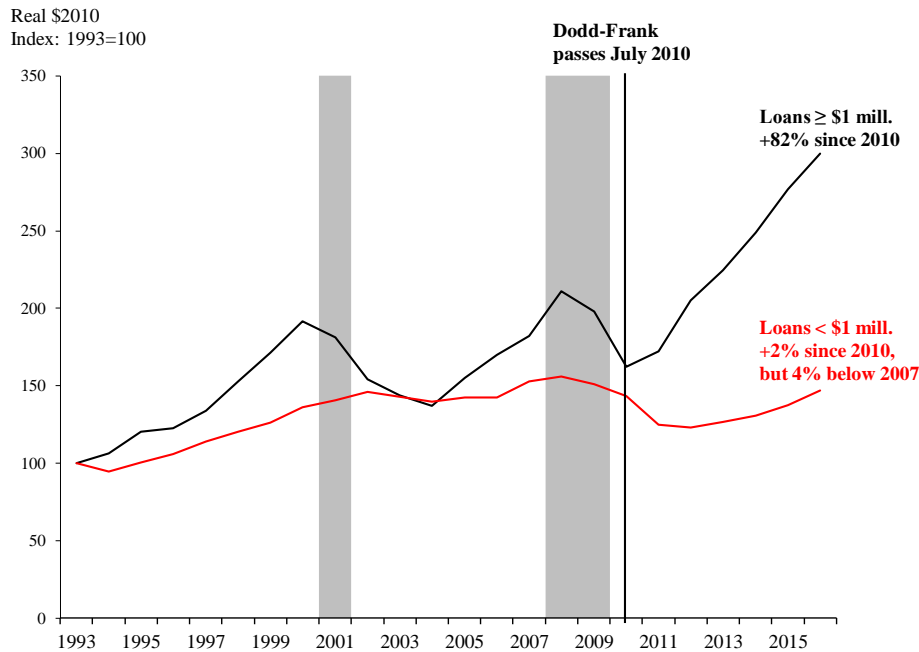


Figure 3: Small C&I Loans Trend Differently from Large Loans Since Dodd Frank is Passed

Sources: Bureau of Economic Advisors, Consolidated Reports of Condition and Income, Federal Financial Institutions Examination Council, and authors' calculations. Aggregate real loans at banks with assets of at least \$300 million—consistently available from 1993-2016 and deflated with the CPI. Shaded areas are recessions.

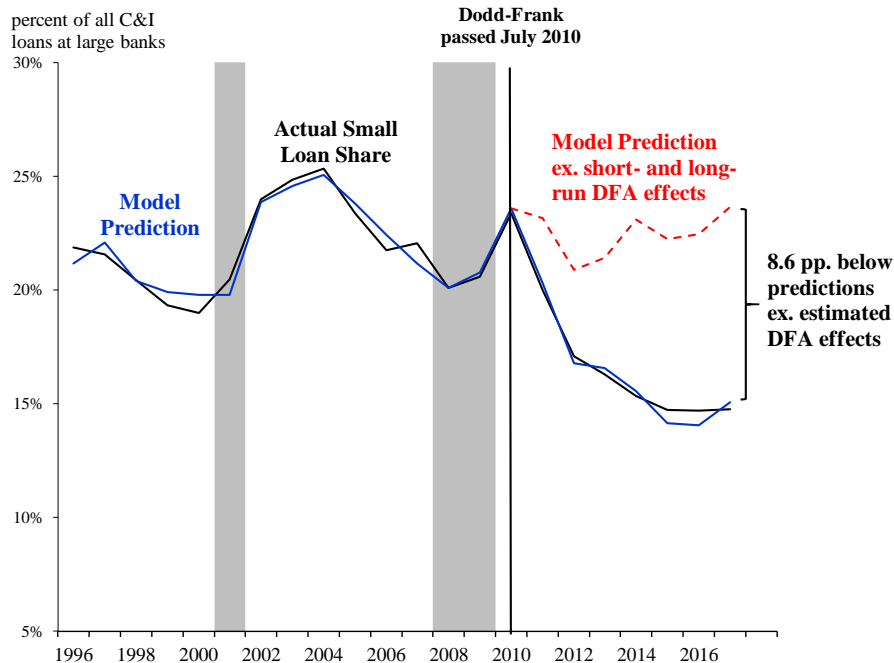


Figure 4: The Small Loan Share of C&I loans Falls At Large Banks After Dodd-Frank

Sources: Consolidated Reports of Condition and Income, Federal Financial Institutions Examination Council, and authors' calculations. Shares at banks with assets of at least \$1 billion (\$2004). Shaded areas are recessions.

trends in the consolidation of the banking system away from small bank. Using annual data (Figure 4) posted declines similar to those in Figure 2, but which cannot be attributed to pre-DFA available since 1993 (described in Section II), we find that the bulk of the post-2010 declines (8.6 percentage points) aggregated for both categories of banks cannot be attributed to business cycle effects or shifts in bank funding cost spreads and appear to have arisen from regulatory reforms enacted since DFA's passage. The estimated magnitude of this regime effect is about twice as much (18 percentage points) for smaller banks. These results shown in Section II are consistent with concerns that an unintended consequence of the DFA has been to reduce small business lending. To address concerns that these findings may merely reflect aggregation bias, Section III examines bank-level data on the small loan share of C&I loans with controls for bank characteristics and year effects, the latter of which pick up cyclical and other time-varying factors.

Consistent with the aggregate category results of Section II, time dummies become negative starting in 2008, then become significantly more negative starting in 2010 and remain so thereafter. To corroborate these findings on small-sized C&I loans, Section III.C (in progress) examines patterns in bank loan extensions to small-sized businesses using CRA data, To further assess whether these loan patterns do not simply reflect loan demand shifts that coincided with the DFA, Section IV examines bank loan officer survey data on changes in credit standards to assess whether the DFA has induced loan supply shifts away from small business lending. Bank survey results (Figure 5) indicate that bank credit standards for making C&I loans became relatively tighter for small businesses compared with medium- and large-sized firms during the period when DFA requirements were most onerous on smaller banking organizations.

As shown in Figure 6, those survey data are consistent with the share of small businesses reporting to the National Federation of Independent Businesses (NFIB) that availability of credit

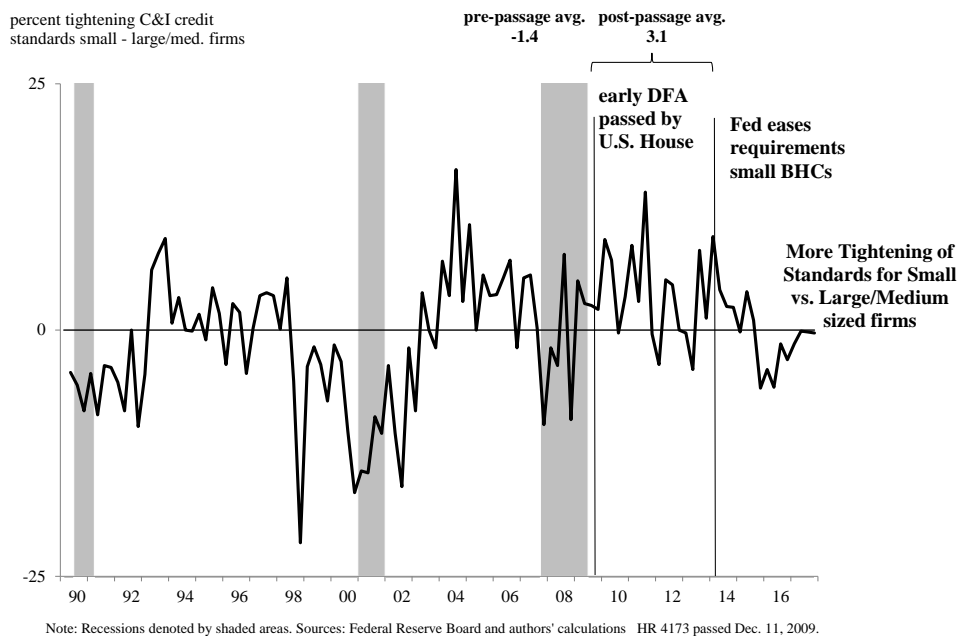


Figure 5: Share Banks Tightening Credit Standards on C&I Loans to Small Firms Minus Share Tightening Credit Standards on Loans to Medium- and Large-Sized Firms.
Sources: Federal Reserve Board and authors' calculations.

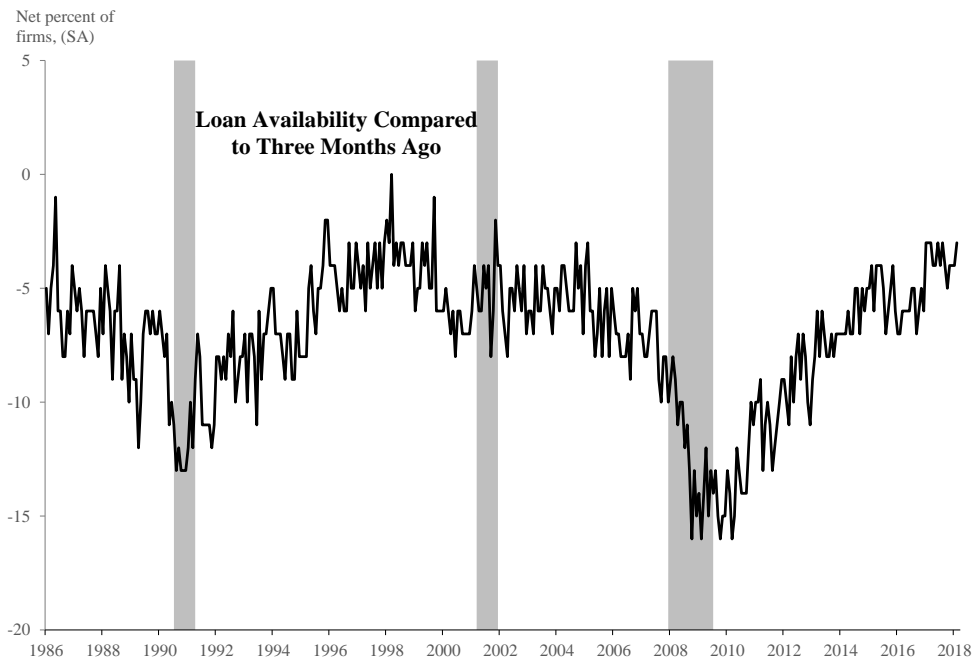


Figure 6: Loan Availability for Small Businesses Unusually Weak in the Great Recession and the Recovery from it.

Source: National Federation of Independent Businesses (NFIB). Net percent of firms seeing loans more minus less available than three months earlier for firms borrowing at least once every three months. Recessions are shaded.

loan supply for small relative to large firms, but has not reversed earlier relative declines induced

had tightened in the prior three months.⁴ Furthermore, lending survey data suggest that regulatory

relief for smaller banking organizations in 2015 may have helped stop a further deterioration of

by the DFA. Section V then assesses whether regulatory steps—namely, the DFA and the overall

number of federal regulations—have played a role in slowing business formation. The last section

of the paper provides perspective on our findings.

II. Analyzing the Small Loan Share of C&I Loans Aggregated by Bank Size Categories

To limit complications from omitting factors that affect business lending in general, we focus on modeling the small business share of C&I loans (*SBS*share, henceforth, referred to as “the small business loan share”), defined as the percent of domestic C&I loans that are under \$1 million

⁴ NFIB data may reflect survivorship bias as there has been some downtrend in the number of survey respondents.

and outstanding. This ratio effectively eliminates common factors that roughly have equal proportional influences on small and all C&I loans. The data are available from the June 30 Call Reports (Consolidated Reports of Condition and Income, Federal Financial Institutions Examination Council, FFIEC) from 1993 to 2017, and allow us to measure the small loan size share midway through each year. Owing to changes in reporting requirements on small banks, we consistently track the small loan size share for three categories of banks.⁵ Because measures based on nominal asset size cutoffs and small banks tend to make a higher share of small-sized business loans, inflation and ongoing mergers—particularly among small banks—can distort the time patterns of these measures. To limit such distortions, we construct annual data on the small loan share at banks for different asset category sizes defined using \$2004 with the CPI.⁶ For 1993-2016, we can track the small loan share at banks with at least \$300 million (\$2004) in total assets (*SBSHAll*), for small banks (*SBSHSmall*) with assets between \$300 million (\$2004) and \$1 billion (\$2004), and for large banks (*SBSHLarge*) having at least \$1 billion (\$2004) in assets. These adjustments allow us to track *SBSHLarge* from 1993-2017 and limits the impact of banks migrating into a large-size category if a fixed nominal asset cutoff were applied to each year.

As shown in Figure 7, the three small loan share series generally move together, but with the small loan share notably higher at small versus the large size banks. Each series moves within a flat range from 1993 through 2010, but then shifts downward over several years to a notably

⁵ There are two breaks in the data collection that need to be taken into account. First, after 2001, banks with assets under \$300 million were no longer required to report data on small loans if all or substantially all of the C&I loans had original volumes under \$100,000. After 2001, fewer small banks under \$300 million in size chose to report, which would impart a spurious downward time trend to the aggregate share if the break is ignored. The second started in 2017, when banks with under \$1 billion were no longer required to distinguish between small sized foreign and domestic C&I loans, while still being required to distinguish between total foreign and domestic C&I loans. This change slightly changes the contours of trends in C&I lending not seen for banks with assets of at least \$1 billion.

⁶ The base year (2004) reflects that data collected under the Community Reinvestment Act (CRA) on originations of loans to small businesses are defined for businesses with at least 1 billion in \$2004. As discussed later in the paper, we plan to use origination data to address one potential concern with using the small loan-size share of C&I loans.

lower range. Using the available full samples for small (1993-2016), all (1993-2016) and large (1993-2017) banks, unit root tests reject stationarity, finding evidence of a unit root in each series. This evidence is consistent with the view that the tougher regulatory regime instituted under DFA has discouraged banks from making small sized loans as argued by Covas (2017), Dahl et al. (2016), and Reichow (2017). Because loan shares are based on outstanding loans, loan contracts are typically multi-year, and it took several years for the relevant agencies to draft precise regulations, the transition of the three loan share variables to the new regime would likely be drawn out as reflected in Figure 7. In addition, the DFA plausibly has a prolonged effect on entry and exit into banking, as suggested by the sharp downshift in the number of new bank charters, from an annual range of 60 to 270 from 1990 to 2008, to about 0 since 2011 (e.g., see McCord, Prescott,

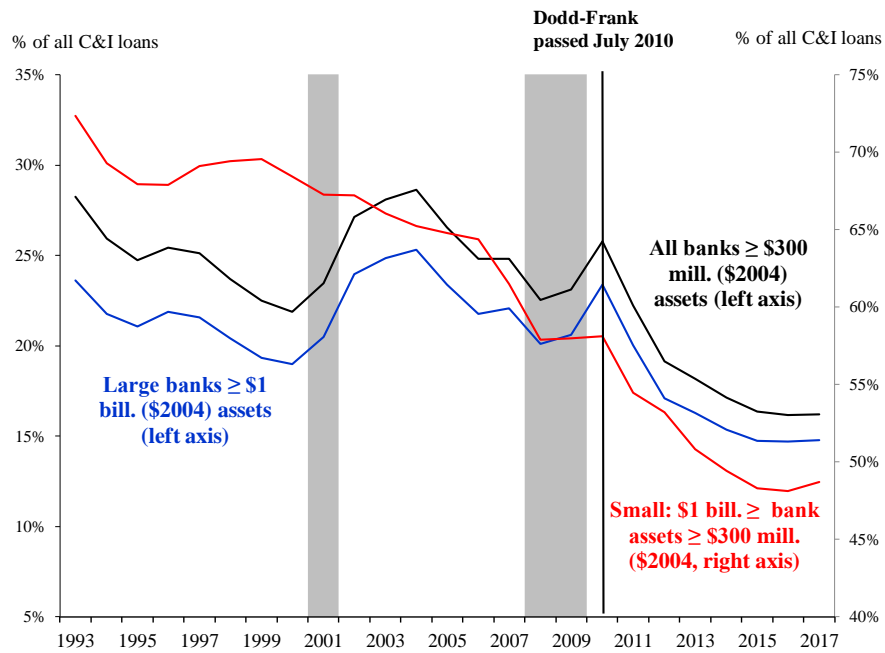


Figure 7: The Small Loan Share of C&I loans Falls After the Dodd-Frank Act

Sources: Consolidated Reports of Condition and Income, Federal Financial Institutions Examination Council, and authors' calculations. Shares at all banks are for those with assets above \$300 million (\$2004), small banks are at least as big but have assets below \$1 billion (\$2004) throughout the sample. Large banks have assets of at least \$1 billion (\$2004) for each year. Shaded areas are recessions.

and Simpson, 2015).⁷

In light of these data patterns, we use cointegration techniques to assess if the DFA regulatory regime has had both long-run and transition (short-run) effects on the small loan size share for each of the three asset categories of banks. We define the new regime with the variable *DFASB*, which equals 0 before 2010, ½ in 2010, and 1 thereafter. Although DFA was passed after the mid-year 2010 Call Report (from which the small loan share readings for that year are constructed), banks likely had a good idea of the basic features of the legislation earlier that year. Reflecting some anticipatory effects, *DFASB* takes a value of ½ in 2010.⁸

To control for business and financial cycle influences we include two variables: the t-1 annual GDP output gap from CBO (*OutputGap*) and the t-1 annual average spread between the three-month dollar Libor and Treasury bill rates (*LiborSP*).⁹ These stationary variables help control for any cyclical influences that may affect the relative volumes of small versus larger C&I loans. A higher Libor spread may reflect greater risk in the banking system and less willingness by banks to undertake risk in lending, consistent with loan supply evidence from Aron et al. (2010) and Bordo et al. (2016). Because small size loans are more typically made to smaller firms that are statistically less apt to survive, a higher Libor spread is likely to be associated with tougher loan supply conditions for small loans. For this reason we expect *LiborSP* to have a negative short-run effect. The sign on *OutputGap* reflects two countervailing influences. If small firms are more apt to fail in recessions, one would expect *OutputGap* to have a positive sign from loan supply

⁷ Preliminary results from a time series model estimated with a long sample (1965-2018) and controls for other regulatory changes and information costs imply that DFA has depressed the per capita number of banks in the U.S.

⁸ In other regressions not shown, this definition outperformed alternative definitions in which *DFASB* equaled 0 in 2010 and 1 thereafter, or 1 since 2010 or 1 since 2009. Note that the models using the paper's definition of *DFASB* attribute the 2010 rise in loan shares to cyclical factors following the Great Recession.

⁹ Owing to the mid-year timing of the loan share series, the t-1 annual data on these variables translate into effects from the t-2 quarterly lags of 4 quarter averages of the variables. This timing outperformed using the t-1 annual readings of the averages of these variables over q3 and q4 readings in year t-2 and q1 and q2 readings in year t-1.

influences. On the other hand, *OutputGap* could have a negative sign if small firms need less temporary lending to survive in booms or if large firms borrow more to fund desired inventory accumulation in booms. In our error-correction framework, we found that alternative financial friction variables, such as spreads between corporate and Treasury bond yields, were insignificant, ostensibly as they are less bank centric than the Libor spread. We also found that alternative business cycle indicators, such as Treasury yield curve spreads and changes in the unemployment rate, were statistically insignificant.

Our error-correction models of small loan share for each bank category are specified as:

$$SBSH_t^e = \alpha_0 + \alpha_1 * DFA_t + \varepsilon_t \quad (1)$$

$$\Delta SBSH_t = \beta_0 + \beta_1 EC_{t-1} + \sum \beta_{2i} \Delta SBSH_{t-i} + \sum \beta_{3i} \Delta DFASB_{t-i} + \beta_4 X_{t-1} + \mu_t \quad (2)$$

where $SBSH_t^e$ is the equilibrium level of small loan share, ε_t and μ_t are i.i.d. residuals, the error correction term $EC_{t-1} = SBSH_{t-1} - SBSH_t^e$, and the vector X_{t-1} of short-run variables includes the t-1 lags of *LiborSP* and *OutputGap*. The estimation of long-run and any short-run relationships is joint following Johansen (1995), and depends on the exogenous short-run factors included (the vector X). In general, we estimated a set of models that include a minimal number of short-run variables and also models with additional highly relevant short-run factors as a robustness check and to address concerns about the choice of such variables. Lag length was chosen to minimize the lags needed to find a unique significant cointegrating variable and, if possible, yield clean residuals. Estimation allows for possible time trends in long-run variables without an independent time effect in the vector aside from measured factors.

Table 1 reports estimates of six models, with two models estimated for each of the three asset size classes of banks, with odd-numbered models omitting the output gap and Libor spread, and the even-numbered models including them. For each model with these cyclical controls, a

unique and significant cointegrating vector is identified, with *DFASB* having a significant, negative long-run impact of lowering the small loan share by 9 percentage points. The magnitude of this effect is about twice as large for small banks, consistent with the view that in addition to raising the fixed costs of making small loans at all banks, DFA's effect is more pronounced at small banks that do not benefit from economies of scale as much as large banks. Of the models lacking such controls, a significant and unique vector was only identified for the small loan share at large banks. To some extent, this may reflect a slightly longer sample period for large banks and that by using a relative size definition to create this subset of banks, it may not be distorted by migration arising from using a fixed nominal cutoff to define it—something affecting the other two bank classes. Consistent with these advantages, the standard error is lowest and the corrected R-square is highest for the large bank model among models with cyclical controls and among those without them. The model for large banks that includes cyclical controls yields model predictions that nicely track the evolution of the small loan share of C&I loans, as shown earlier in Figure 4.

In every model of changes in the small loan share, the error-correction term is at least marginally significant with a negative sign indicating that short-run movements tend to reduce disequilibria. In the models with both cyclical controls, the error-correction term is significant at the 99 percent confidence level, with annual speeds of 43 to 53 percent at all and large banks, respectively, and a slower but still significant speed of 27 percent for small banks. In every case, the Libor spread has a negative and significant effect. While the output gap is always significant, it has a positive sign for the small bank subset and a negative one for all and large bank groupings. This difference plausibly reflects the balance of the earlier mentioned countervailing effects. When output gaps are high in strong business cycle upswings, small banks that typically have very few large clients, may likely ease credit standards for loans to small firms. At large banks,

borrowing by large firms to build up desired inventory levels may lead larger firms to borrow more when the output gap is very positive and this effect may outweigh any increased borrowing by small firms, thereby pushing down the small loan share in periods of high positive output gaps at large banks (which dominate loan volumes for the banking industry).

We also tested the robustness of our key findings to controlling for other factors that might explain or account for the time series behavior of the small loan share. These include using two different ways of controlling for migration of loans from one nominal loan size category to another, as well as including controls for the aging of the U.S. population and possible hysteresis-like effects from the financial damage to households from the Great Recession and the financial and housing crisis of the late 2000s. As discussed in more detail in Appendix A, our key finding that the DFA has lowered the small loan share is robust to including controls for these effects.

III. Analyzing Bank-Level Data on the Small Loan Share of C&I Loans

Because the data in Section II aggregate across banks of different sizes, they internalize any substitution among banks, and thus reflect a negative, reduced-form net impact of DFA across all banks. Nevertheless, in principle, these findings could merely reflect aggregation bias or spurious correlation from using aggregate time series-analysis.

III.A. Analyzing Bank-Level Data on the Small Loan Share of C&I Loans Outstanding

To address these concerns and shed more light on how DFA may have affected small business lending, this section first examines bank-level data on the small-loan share of C&I loans with controls for time-varying bank characteristics and both bank and year fixed effects, the latter of which pick up cyclical and other time-varying factors. As in Section II, we use data from FFIEC Call Reports, but now assess the behavior of the small loan share at the bank level for several asset size categories of banks: all, under \$300 Million, \$300 Million-\$1 Billion, \$1 – \$10 Billion, and

over \$10 Billion in size, all in \$2004. The bank-level data are adjusted for mergers.¹⁰ We assess the long-run behavior of the small loan share of C&I loans in a panel setting by estimating the following model with bank level data:

$$SBSH_t = \alpha_0 + \alpha_1 * SBSH_{t-1} + \alpha_2 * X_{t-1} + \alpha_3 * BANKDummies + \alpha_3 * TIMEDummies + \varepsilon_t \quad (3)$$

where *TIMEDummies* denotes a set of dummies for all years (denoted as *d1995*, ... *d2017*) except the base year 2009, *BANKDummies* denote a set of bank fixed effects that are included but are absorbed (and not shown in Tables), and *X* is a vector of controls for individual balance sheet characteristics. The latter include the *t-1* dated lag of total deposits to total assets (*L_tdta*), total equity to total assets (*L_eqta*), non-performing loans to total assets (*L_npa*), liquid assets to total assets (*L_liqta*), and unused bank loan commitments relative to the sum of assets and commitments (*L_bcommittac*). (In the current table, *SBSH_{t-1}* is denoted as *L_sharecni0*.) *t*-statistics are based upon robust standard errors clustered at the bank level and “R-squared” is the “within” R-squared.

Several notable patterns in the time dummies are evident in the regressions as shown in Table 2. For all size categories of banks, the individual yearly dummies tend to be statistically or marginally significant from 1995 through 2003. This likely reflects a revival of small business lending during the strong expansion of the late 1990s that had followed the credit crunch of the early 1990s, which was associated with the transition to the Basel 1 capital requirements. The continued robustness during the mild recession of the early 2000s plausibly owes to the easy monetary policy of that time coupled with the needs of small business to finance inventories during that period of weak economic performance. The yearly dummies tend to be insignificant and near

¹⁰ To account for the impact of mergers on the balance sheets of acquiring banks, we use the following procedure. The acquirer and target are identified, as well as the date of each acquisition, using information FDIC certificate information obtained from the FDIC’s Institution Directory—the third primary source of data for the current study. This information is used to combine the values of each dollar-denominated item for merging banks reported in the period prior to the merger.

zero during the mid- to late expansion of 2004-07 when monetary policy had shifted from easy to slightly restrictive, before turning significantly negative for most banks in 2008, the first year of recession (recall that the yearly data are mid-year readings).

The yearly dummies become even more negative in 2010 (the year DFA passed) and a little more so in 2011, ostensibly reflecting a further adjustment to DFA. Then for all banks and for each size category except for banks with assets more than \$10 billion (\$2004), the negative magnitudes of the yearly dummies remain near their 2011 coefficient estimate or become a little more negative. As with the results in Section 2, this pattern is consistent with concerns that the post-2009 weakness in small business lending is not primarily cyclical in nature, but rather owes to a persistent negative influence, such as the DFA. In contrast, for the largest banks with assets of at least \$ 10 billion (\$2004), although the yearly dummies continue to have negative coefficients after 2010, the coefficients become smaller in magnitude and become statistically insignificant. This pattern accords with the view that increased compliance costs were especially burdensome for all but the largest banks owing to diseconomies of scale at banks less than \$10 billion in assets.

III.B. Analyzing Bank-Level Data on the Small Loan Share of C&I Loans Outstanding

To allay concerns that DFA may have simply induced banks to make fewer but larger sized loans to small businesses, we examine in a second subsection (in process) another source of data on bank loan originations to small-sized bank business borrowers. Scaling these originations by the previous year's level of total business loans, we model scaled originations of small business loans as a function of the same set of bank characteristics and year effects used in Section IIIA to model the small loan share of C&I loans outstanding. Preliminary estimates through 2015 find a very similar pattern of negative, post-2009 year effects that are persistent. These results

demonstrate that bank lending to small businesses did in fact decline following the passage of DFA and that the loan origination findings for small firms are consistent, with the loan outstanding findings for the share of small-sized business loans.

III.C. Analyzing Bank-Level Data on C&I Loan Extensions to Small Businesses

(in progress, anticipate results for presentation on March 1).

IV. Evidence from Bank Credit Standards for C&I (Business) Loans

Results from Sections II and III are from reduced-form models, which may not provide fully convincing proof that the DFA affected the loan supply channel. In particular, if the DFA raised the fixed costs of making business loans, then the DFA would directly reduce the supply of small-sized loans relative to other loans at each bank. In addition, because the DFA's cost impact has induced a disproportionate consolidation of smaller banks, whose C&I loan portfolios are more heavily weighted toward small-sized business loans, the DFA indirectly reduces loan supply more for small-sized loans than for larger-sized loans by directly decreasing the prevalence of small banks. Both the direct and indirect effects imply the testable hypothesis that the DFA would induce C&I loan standards to be tightened more for C&I loans to small-sized firms than to larger firms.

To assess this empirical implication—which also tests for a loan supply impact of the DFA—this section examines quarterly data from the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending Practices which, since 1990:q3, has asked banks about how their credit standards for C&I loans to different size firm categories have changed relative to three months earlier. We define the relative change in credit standards on small versus large firms (ΔCS_{Gap}) as the net percent change in banks tightening credit standards on C&I loans to small-size firms minus that on loans to medium- and large-size firms. This variable is stationary and we regress it on a set of stationary variables.

Following Aron, et al. (2010) and Bordo, et al. (2016), potential variables for modeling $\Delta CSGap$ are based on implications from the screening model of Stiglitz and Weiss (1981, part IV). That model implies that credit standards on a particular type of loan would be tightened if the real federal funds rate (the riskless real rate) rose, the economic outlook worsened (perhaps proxied by the percent change in the leading economic indicators), loan quality diminished (perhaps proxied by the change in loan delinquency rates), or if the burden of bank regulation rose (which effectively raises banks' cost of making loans). Aron, et al. (2010) and Bordo, et al. (2016) track these respective general types of variables with the change in the real federal funds rate (ΔRFF), the percent change in the index of leading economic indicators ($\Delta^2 LEI$), the year-over-year change in consumer installment or overall delinquency rates ($\Delta^4 DEL$) rose, and pre-1983 bank regulations (Aron, et al., 2012) or economic policy uncertainty (Bordo, et al., 2016), respectively.¹¹ Aron, et al. also include the change in the 3-month LIBOR-Treasury interest rate spread ($\Delta LiborSp$) to control for changes in banks' marginal funding costs beyond those tracked by changes in the real federal funds rate, while Bordo, et al. (2016) use a dummy for the failure of Lehman in their shorter time series sample. We found that the change in the spread between Aaa-rated corporate and 10-year Treasury bond yields ($\Delta AaaTR$) outperformed $\Delta LiborSp$, perhaps reflecting distortions to the latter spread from Federal Reserve interventions in providing new lender-of-last-resort facilities during the crisis and false reporting of individual bank rates that were later used to calculate LIBOR. For a variable like $\Delta CSGap$, which tracks the difference in changes in credit standards, such variables would only be significant if they affected the relative setting of credit standards on the small- versus large-firm categories. We regressed $\Delta CSGap$ on the same definitions of ΔRFF ,

¹¹ ΔRFF is the first difference of the nominal federal funds rate minus the year-over-year percent change in the personal consumption expenditures deflator. $\Delta^2 LEI$ is the percent change in the Conference Board's index of leading economic indicators between, t-2 and t. $\Delta^4 DEL$ is the year/year change in C&I delinquency rates (Federal Reserve Board data).

Δ^2LEI , and $\Delta AaaTR$. For Δ^4DEL we instead tried the year-over-year change (and various shorter changes) in the Federal Reserve Board series on C&I loan delinquency rates at all banks.

For regulatory variables, we included a dummy for the first period of Dodd-Frank (*DFASBI*). This variable equals 1 from the quarter (2009:q4) when the original version of the DFA was approved by the U.S. House of Representatives through 2014:q3, just after which the Federal Reserve announced that it would ease the regulatory burden of the DFA on smaller banks starting in early 2015. The timing of the DFA effects is faster in our model of credit standards than of loan shares because the former more quickly reflects banks' anticipation of future conditions affecting loan returns whereas loans outstanding tend to move with a lag after loan policy changes and reflect the stock of outstanding loans rather than terms on new loans.

As noted by Hunter (2015), the Federal Reserve's tailoring of the DFA to smaller depositories in 2015:q1 included 1) allowing small savings and loan associations to meet easier debt limitations that small banks enjoyed; 2) expanding easier debt limits for depositories with under \$500 million in assets to a higher threshold of under \$1 billion in assets; 3) eliminating a number of quarterly and complex financial reporting requirements for many institutions; and 4) eliminating many detailed capital items for small savings and loan associations.¹² For the less stringent period of the DFA, we include a shift dummy to control for any remaining effect of the DFA on credit standards for loans to small versus large firms. This variable, *DFASB2*, equals 1 only since 2014:q4. If the Federal Reserve's 2014 announcement provided regulatory relief that

¹² For the third and fourth numbered actions, Hunter (2015) lists eliminating "quarterly and more complex consolidated financial reporting requirements (FR Y-9C) for approximately 470 of these institutions, and instead required parent-only financial statements (FR Y-9SP) semiannually;" and eliminating "all regulatory capital data items that were to be reported on the FR Y-9SP for approximately 240 savings and loan holding companies with less than \$500 million in total consolidated assets."

affected relative credit standards, the magnitude of the coefficient on *DFASB1* should exceed that of the one on *DFASB2*.

We regressed $\Delta CSGap$ on the full set of variables, and took the approach of progressively dropping the least significant of the insignificant variables. Only $\Delta^2 LEI$ was dropped, leaving the following baseline and regulatory specifications:

$$\Delta CSGap_t = \beta_0 + \beta_1 \Delta RFM_{t-1} + \beta_2 \Delta^4 DEL_{t-1} + \beta_3 \Delta AaaTR_{t-1} + \varepsilon_t \quad (4)$$

$$\Delta CSGap_t = \beta_0 + \beta_1 \Delta RFM_{t-1} + \beta_2 \Delta^4 DEL_{t-1} + \beta_3 \Delta AaaTR_{t-1} + \beta_3 DFAl_t + \varepsilon_t \quad (5)$$

$$\Delta CSGap_t = \beta_0 + \beta_1 \Delta RFM_{t-1} + \beta_2 \Delta^4 DEL_{t-1} + \beta_3 \Delta AaaTR_{t-1} + \beta_3 DFASB1_t + \beta_3 DFASB2_t + \varepsilon_t \quad (6)$$

Table 3 reports results for estimating several models, all of which include an AR(1) correction for serial correlation in the residuals. The baseline Models 1 and 2 estimate equation (3) over the full (1990:q3–2017:q1) and pre-DFA (1990:q3–2010:q2) samples, respectively. Using the full sample, Model 3 estimates equation (5) that adds *DFAl* to the baseline model, and Model 4 estimates equation (6) that adds *DFASB1* and *DFASB2* to the baseline model.

There are several common patterns across all of the models. First, *ARFM* generally has at least a marginally significant, positive coefficient whose magnitude implies that a one percentage point rise in the real federal funds rate induces two percent more banks to tighten credit standards on loans to small businesses than on loans to larger entities.¹³ *AAaTR* has a negative, significant sign implying that a widening of this risk premium induces relatively less tightening of credit standards on loans to smaller businesses. The negative signed effect is plausible because larger

¹³ *ARFM* outperformed an alternative funds rate measure accounting for unconventional monetary policy. In other regressions which replaced *ARFM* with the first difference of Leo Krippner’s shadow federal funds rate measure minus the same PCE inflation adjustment and found notably worse model fits with DFA and SOX terms remaining significant. This may reflect that bankers’ incentives to make C&I loans are more driven by short-term funding rates and are positively related to the slope of the yield curve but are less stimulated by quantitative easing which (lowers the shadow fed fund rate), by lowering long-term interest rates, tends to flatten the yield curve, diminishing the gains from banks borrowing short from depositors and lending at medium to long-term loan interest rates.

banks tend to rely more on borrowed funds and tend to make relatively fewer loans to small businesses. Ostensibly, as the cost of borrowed funds rises, it raises funding costs more at larger banks, which induces a tightening of credit standards more prevalent on loans to larger business than to smaller ones. Another pattern is that Δ^4DEL has a negative and significant sign, implying that a rise in the nation-wide C&I delinquency rate induces relatively less tightening of credit standards on loans to smaller businesses. This could reflect that a value-weighted national delinquency rate is more reflective of loan quality for nationally exposed larger banks that make relatively fewer loans to small businesses and more to larger firms.

With respect to the effects of the DFA, the dummy for the most stringent period of the DFA on small banks, *DFASB1*, is statistically significant and positive in Models 3 and 4. The magnitude of the estimated coefficient implies that the DFA induced four percent more banks to tighten credit standards on loans to small firms than on loans to larger ones. This effect is economically significant insofar as it occurs, on average, for each quarter from 2009:q4 to 2014:q3, implying a large cumulative effect that is consistent with the results for the small-sized loan shares outstanding reported in Sections II and III. The variable (*DFASB2*) controls for the possible effects of the DFA, starting with the Federal Reserve's late 2014 announcement of regulatory easing moves, and is insignificant and close to zero. This suggests that the regulatory relief measures had helped stop the DFA from further disproportionately affecting small business lending. However, the lack of a positive and significant coefficient suggests that the actions have not reversed the earlier relative tightening of credit standards on C&I loans to small- versus large-sized businesses. Overall, the results indicate that the DFA did reduce the supply of loans more for small businesses than for larger firms, and that regulatory relief for smaller depositories has stabilized the relative level of credit availability for small versus larger businesses that occurred from 2010 to 2014.

V. Financial Regulation and Business Formation

Thus far, the evidence presented shows that the DFA has reduced both the share of C&I loans that are small-sized and the relative supply of bank loans to small versus larger firms. Comprehensive time series data on all sources of funding to nonpublic firms, however, are not available to assess to what extent bank lending effects from the DFA have been offset by increased use of nonbank sources of funding, such as private equity or loans from nonbanks. As an alternative way to analyze the net and real effects of the DFA on small business, we assess whether financial regulations, such as the DFA, have altered the pace at which new firms are formed.

As stressed by several studies, most notably Decker, et al. (2014, 2016a), there has been a notable decline in U.S. business creation that predates the Great Recession. More recent papers have studied some of the macroeconomic ramifications of the slowdown in business entry. For example, because productivity grows rapidly early in the life cycle of firms, slower business entry can lower the aggregate pace of productivity growth, contributing to the downshift in long-run growth since the early 2000s, as argued by Alon, et al. (2017). Likely compounding the impact of reduced entry rates on innovation and economic growth is the marked decrease in the share of new firms that have subsequently grown rapidly (Decker, et al. 2016b) and which had often been funded by venture capital in much of the 1980s and 1990s (Gornall and Strebulaev, 2015).

We use quarterly data spanning 1993:q1-2017:q4 from the Bureau of Labor Statistics (BLS) to track the birth rate (*Birth*) of new private establishments in the U.S. (BLS uses data on firm births and deaths to adjust payrolls at sampled firms to estimate nonfarm payroll employment.) Because smaller firms tend to be younger, there are parallels between modeling small business lending and business formation. For example, as shown earlier in Figure 1, the quarterly birth rate was unusually depressed from the onset of the Great Recession to late 2014. While annual data are available back to 1983 (and allow for some disaggregation by industry), the

greater number of degrees of freedom using quarterly data are more suitable given the short time span covered and the time series aspects of the regulatory variables considered.

Because there are no published time series models of the birth rate, we experimented with various time series data to build simple empirical models of this stationary series. We found two consistently significant time series variables: the change in the civilian unemployment rate (ΔU) and the change in the spread between yields on Aaa-rated corporate and 10-year Treasury bonds ($\Delta AaaTr$). The former helps control for the cyclical impact of economic slack on entrepreneurs' incentives to expand capacity and to undertake entrepreneurial risk, while the latter helps to more directly control for the cyclical influences of risk on entrepreneurs' incentives to start new firms. Both variables, via gauging cyclical influences on creditors' or investors' incentives to provide external finance, likely also track cyclical changes in entrepreneurs' ability to obtain external funding.

To these we add three regulatory variables to assess whether regulations in general and on banks affected the pace of business formation. Two are *DFASB1* and *DFASB2*, which track the impact of the two phases of the DFA on the overall availability of bank credit to entrepreneurs that may stem from the effects of regulations not only on C&I lending, but also on access to consumer and real estate loans, which small businesses might also use for funding. These two bank regulation variables are supplemented with a more general, time series measure of the number of federal regulations. Specifically, annual data on the total number of pages in the code of federal regulations (source: Federal Register) are interpolated into quarterly series using a cubic spline and then are scaled by the population. The resulting series, *RegPerCap*, is a proxy for the per capita federal regulations, and it turned up in the early and mid-2000s before both the Great

Recession and the DFA.¹⁴ Nevertheless, because the series is dominated by a time trend, another model replaces *RegPerCap* with a time trend to test the two DFA dummy variables.

Finally, we also track the time-varying incentive to start businesses with a measure of Tobin's q. Specifically, we measure Tobin's Q with the ratio (*TobinsQ*) of the stock market capitalization of nonfinancial corporations to the replacement cost (historical basis) using Federal Reserve data from the Financial Accounts of the U.S. The t-3 lag fit the data best and reflect a reasonable lag of the effect of stock prices on entry.

To test for the possible effects of DFA on business formation, we add the two DFA variables to a simple time series model of the firm birth rate which includes a proxy for Tobin's q along with controls for the short-run business (ΔU_{t-1}) and financial cycles ($\Delta AaaTr_{t-1}$):

$$\begin{aligned} Birth_t = & \beta_0 + \beta_1 \Delta U_{t-1} + \beta_2 \Delta AaaTr_{t-1} + \beta_3 TobinsQ_{t-2} + \beta_4 DFASB1_t + \beta_5 DFASB2_t \\ & + \beta_6 RegPerCap_{t-1} + \varepsilon_t \end{aligned} \quad (7)$$

where $\beta_3 > 0$, while β_1 , β_2 , β_4 , and β_6 are expected to be negative. β_5 may or may not be negative, depending on how much changes in DFA implementation rules may have eased banks' regulatory burden in making small business loans.

Table 4 presents results from estimating eight versions of eq. (7) using establishment birth rate data available since 1993:q2. Each of these models include a correction for first order autocorrelation in their residuals and are estimated through 2017:q2 to reflect the availability of *RegPerCap*. The first three specifications do not include a role for Tobin's Q, while Models 4-8 include Tobin's Q effects. Model 1 estimates eq. (7) over the full sample (1993:q2–2017:q4)

¹⁴ In examining CPS data, Kozeniauskas (2017) finds that entrepreneurship rates among households have fallen across all ages, and in a calibrated model of endogenous business formation, he demonstrates that higher fixed entry costs could plausibly for much of the slowdown in business entry rates. Greater regulations can plausibly raise entry costs.

omitting the three regulatory variables. Model 2 re-estimates Model 1 but adds a time trend. Model 3 omits a time trend like Model 1, but includes the three regulatory variables. Model 4 adds the Tobin's Q variable to Model 1, but omits the regulatory variables. To Model 4, Model 5 adds the three regulatory variables. Model 6 repeats Model 5 except that it drops the insignificant second period DFA variable, *DFASB2*. Model 7 replaces the broad regulation variable *RegPerCap* with a simple time trend, while model 8 omits both the time trend and *RegPerCap*, but includes the DFA variables.

Several patterns emerge across Table 4. First, the models omitting the DFA variables (Models 1, 2, and 4) have serial correlation in errors and have poorer fits than any model which includes those variables. Second, in the other models, the DFA dummy for the most stringent periods is at least marginally significant and negative, and is significant at least the 95 percent confidence level in models that include the significant Tobin's Q variable. Third, with the exception of Model 8, which omits both the time trend and *RegPerCap*, the DFA dummy for the post 2015:q1 period is insignificant. This provides weak evidence suggesting that if the DFA is still slowing business formation, the effect is less than it was before some DFA regulations on smaller banks were eased. Nevertheless, standard errors imply that the difference between the coefficients on *DFASB1* and *DFASB2* is not significant. Fourth, the time trend and *RegPerCap* are negative and highly significant in the models that include one of them. In a model including both (not shown in Table 1), the time trend remains significant, while *RegPerCap* is insignificant. Based on this finding, Model 7 includes both DFA variables and the time trend, but omits the broad gauge of federal regulations. Nevertheless, in models that include just one of the significant time trend or *RegPerCap* variables, *DFASB1* has a significant and negative coefficient, while *DFASB2* is insignificant. Only in the model (Model 8) that omits both the time trend and *RegPerCap* is the

DFASB2 variable significant. However, Model 8 does not fit as well as the other Tobin's *q* models that include either significant variable (Models 5-7), and *DFASB2* is insignificant in those preferable models.

Finally, in regressions not shown, our results in Models 5-7 regarding the significance of *DFASB1* and the insignificance of *DFASB2* were robust to including a control for wealth hysteresis effects. In particular, we included a variable for household wealth (the wealth-to-disposable income variable in the Financial Accounts of the U.S.), which could help control for hysteresis effects from the damage to wealth from the Great Recession and the financial and housing crisis. This was insignificant, perhaps reflecting multi-collinearity with the inclusion of wealth effects via the Tobin's *q* variables. In other runs not shown, we also included the growth rate of the working age (age 25 to 54) population to control for possible effects of slowing population growth among those at a life-cycle stage conducive to forming a business. This also proved insignificant, possibly because the slowdown in working age population growth began in the early 1990s—nearly a decade before the slowdown in business formation that began during the early 2000s.¹⁵

V. Conclusion

Owing to economies of scale, the increased fixed costs of complying with loan regulations have reduced the incentives for individual banks to make small-sized loans (Covas, 2017) and have induced greater consolidation of the banking industry (Dahl, et al., 2016, and Reichow, 2017), away from small banks that disproportionately have lent to small businesses. Consistent with concerns that the DFA has induced the banking industry to reduce lending to small businesses, we find strong evidence of a break in the downward trend in the small business share of C&I loans

¹⁵ Although the Affordable Care Act (ACA) also passed in 2010, it unlikely accounts for the estimated DFA effects for three reasons. First, many small firms were exempt from the ACA's requirements for employers to provide health insurance. Second, the implementation of the ACA occurred well after the large downshift in small loan share in 2011. Third, ACA effects cannot really account for the differential effects of the DFA on changes in bank credit standards and on business formation before and after regulatory relief from the DFA was announced in 2014.

that coincides with the passage of the DFA. The inclusion of controls for the business cycle along with the asynchronous timing of the economic recovery and the plunging small business loan share imply that most of the recent downtrend stems more from the DFA-induced regulatory response to the Great Recession rather than the non-regulatory impact of that downturn. Since 2010, the small business share of C&I loans has fallen by 9 percentage points, and our results indicate that the vast bulk of this decline is linked to the passage of the DFA.

Other results indicate that banks credit standards for making C&I loans became relatively tighter for small businesses compared with medium- and large-sized firms when DFA requirements were most onerous on smaller banking organizations. This set of findings implies that the DFA induced loan supply shifts away from small business lending. This further indicates that our findings on outstanding loans are not simply reflective of loan demand shifts that coincided with the DFA. Furthermore, survey data on bank loan supply suggest that regulatory relief for smaller banking organizations in 2014 may have helped stop further intensification of the negative, unintended impact of the DFA on small business lending. In this way, our findings are loosely supportive of efforts to refine the DFA to better tailor it to the costs and benefits of regulating community banks as discussed by Hunter (2015) and Yellen (2016).

Partly to assess whether the negative effects of the DFA on small business lending were offset by increased use of other funding sources, we also analyze whether the timing of the DFA has affected the pace of business formation. Our study also provides evidence that the early stages of the DFA had a large negative effect on business entry, in contrast to a smaller and mainly insignificant negative effect in latter stages, when small banks were granted some exemptions from some provisions of the DFA.¹⁶ Furthermore, we find timing patterns indicating that the relative

¹⁶ While our results are unclear about how to gauge the impact of other regulations, the findings consistently indicate that the timing of the early stage, tougher implementation of DFA is correlated with otherwise unexplained

tightening of bank credit standards on small versus large firms abated and the rate of business formation may have partly revived following efforts to provide regulatory relief to smaller banks via modified rules implementing the DFA. In contrast, results using either a simple time trend or a gauge of regulations per capita suggest that other factors are still restraining business formation.

While we show evidence of some downside aspects of the DFA, our study should not be misinterpreted as providing evidence against other aspects of the DFA for which there is consensus of positive net benefits (e.g., higher capital requirements and stress tests for large institutions). Data limitations restrict how much one can infer from analyzing—in isolation—any one of the three aspects of small business activity examined here. However, when viewed together, findings on small business loans, bank lending supply policies, and small business formation provide consistent evidence that increased regulation from the Dodd-Frank Act has had the unintended consequence of impairing small business activity in the U.S.

weakness in business formation. Using a time trend yields a better fitting model, but, compared to the per capita gauge of federal regulations, a time trend is arguably less linked to factors that can deter business formation.

Table 1: Annual Models of the Small-Sized Loan Share of C&I Loans, 1995-2017

Long-Run Equilibrium: $SBSH_t = \alpha_0 + \alpha_1 DFASB_t + \varepsilon_t$

Variables	Bank Asset Size Classes					
	All		Large (assets>\$1B)		Small (300M<assets<\$1B)	
Model No.	1	2	3	4	5	6
Constant	0.2541	0.2617	0.2223	0.2294	0.8109	1.039
$DFASB_t$	-0.0795** (7.14)	-0.1050** (11.95)	-0.0649** (4.37)	-0.0882** (11.02)	-0.0932** (8.50)	-0.0836** (10.56)
$Time_t$					-0.0054** (7.71)	-0.0073** (11.09)
unique coint.	No	Yes**	No	Yes**	Yes**	Yes**
vec. # lags	2	2	1	2	1	1
trace no vec.	13.41	26.44**	15.49	24.75**	29.31**	43.63**
trace only 1	0.70	2.60	3.84	3.12	5.90	1.77
Short-Run: $\Delta SBSH_t = \beta_0 + \beta_1 EC_{t-1} + \sum \beta_{2i} \Delta SBSH_{t-i} + \sum \beta_{3i} \Delta DFASB_{t-i} + \beta_4 X_{t-1} + \mu_t$						
EC_{t-1} , 'adjustment speed'	-0.619** (3.52)	-0.391** (3.60)	-0.412* (2.56)	-0.432** (3.77)	-0.211 (1.40)	-0.261* (2.19)
$\Delta SBSH_{t-1}$	0.594** (2.95)	0.659** (5.24)	0.315* (2.01)	0.681** (5.59)	0.276 (1.35)	0.210 (1.12)
$\Delta DFASB_{t-1}$	-0.039 (1.64)	-0.019 (1.19)	-0.024 (1.02)	-0.019 (1.31)	-0.020 (1.05)	0.007 (0.04)
$BaaTR10_{t-1}$		0.010* (2.54)		0.011** (2.92)		
$\Delta^2 LEI_{t-1}$ $X100$		-0.156** (4.92)		-0.153** (4.51)		
$D2008_t$		-0.024** (3.17)		-0.021** (2.91)		-0.031** (4.17)
Constant	-0.001 (0.48)	0.025* (2.61)	-0.001 (0.29)	0.029** (2.96)	-0.005+ (1.61)	-0.000 (0.01)
Adj. R ²	0.541	0.840	0.457	0.858	0.146	0.495
S.E.x100	1.178	0.695	1.188	0.620	1.172	0.901
VEC Auto (1)	4.01	4.90	9.38+	4.82	3.54	1.42
VEC Auto (2)	4.02	3.08	7.92+	2.86	3.89	3.58

Notes: (i) Absolute t-statistics in parentheses. ** (*) significant at the 99% (95%) confidence level. (ii) Long-run: Maximum likelihood estimates of the long-run equilibrium relationship using a two-equation system with at most one cointegrating vector. (iii) $EC_{t-1} = SBSH_{t-1} - \alpha_0 - \alpha_1 DFASB_{t-1}$. (iv) First difference terms of elements in the long-run cointegrating vector. (v) Lag lengths chosen to minimize the AIC criterion. (vi) significance of the trace and VEC Auto statistics reflects lag length and if a time trend is included in the long-run.

Table 2: Bank-Level Models of the Small-Sized Share of C&I Loans By Bank Asset Size, 1995-2017

Regressions Explaining SBL C&I (< \$1 Million) Share of Total C&I by Bank Size in 2004 USD

VARIABLES	All Banks			Banks < \$300M			Banks \$300M - \$1B			Banks \$1B - \$10B			Banks > \$10B			Banks > \$1B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	sharecni0 Coef.	Std. Error	t-Statistic	sharecni0 Coef.	Std. Error	t-Statistic	sharecni0 Coef.	Std. Error	t-Statistic	sharecni0 Coef.	Std. Error	t-Statistic	sharecni0 Coef.	Std. Error	t-Statistic	sharecni0 Coef.	Std. Error	t-Statistic
sharecni0																		
Lsharecni0	0.698	0.006	114.70	0.685	0.006	112.70	0.518	0.044	11.91	0.524	0.045	11.75	0.651	0.058	11.25	0.566	0.040	14.25
Ltdta	0.018	0.003	5.29	0.016	0.004	3.64	0.009	0.009	1.04	0.014	0.012	1.16	0.004	0.010	0.45	0.011	0.009	1.16
Leqta	0.001	0.011	0.09	-0.001	0.012	-0.11	0.008	0.026	0.32	0.049	0.045	1.09	0.046	0.026	1.78	0.057	0.038	1.50
Lnpa	-0.043	0.008	-5.13	-0.055	0.010	-5.27	-0.053	0.021	-2.55	0.023	0.036	0.65	0.028	0.092	0.30	0.038	0.037	1.05
Lroa	0.002	0.026	0.07	0.002	0.034	0.05	-0.053	0.048	-1.10	-0.037	0.080	-0.46	-0.094	0.101	-0.94	-0.030	0.073	-0.41
Lliqta	0.000	0.002	0.14	0.000	0.002	0.18	-0.009	0.005	-1.79	-0.007	0.007	-1.09	-0.009	0.008	-1.21	-0.007	0.005	-1.39
Lbcommittac	-0.019	0.005	-4.21	-0.014	0.006	-2.28	-0.021	0.010	-1.99	-0.020	0.010	-2.01	-0.024	0.017	-1.42	-0.023	0.008	-2.79
y1995	0.008	0.001	12.82	0.008	0.001	10.28	0.015	0.002	6.58	0.008	0.002	3.59	0.007	0.003	2.47	0.007	0.002	4.08
y1996	0.008	0.001	12.90	0.007	0.001	10.06	0.016	0.003	6.06	0.014	0.002	6.14	0.005	0.003	2.00	0.012	0.002	7.26
y1997	0.006	0.001	9.06	0.005	0.001	6.53	0.014	0.002	6.52	0.010	0.002	3.95	0.006	0.002	2.61	0.009	0.002	4.90
y1998	0.007	0.001	10.07	0.006	0.001	7.49	0.015	0.002	6.96	0.011	0.002	4.92	0.008	0.003	2.47	0.010	0.002	5.80
y1999	0.007	0.001	11.61	0.007	0.001	9.64	0.014	0.002	7.82	0.009	0.002	4.40	0.005	0.003	1.60	0.008	0.002	4.62
y2000	0.006	0.001	9.78	0.006	0.001	8.78	0.011	0.002	6.66	0.008	0.002	3.85	0.006	0.004	1.70	0.007	0.002	4.04
y2001	0.006	0.001	9.41	0.006	0.001	7.93	0.011	0.002	4.76	0.013	0.003	4.75	0.005	0.004	1.48	0.011	0.002	4.91
y2002	0.001	0.001	1.37	0.001	0.001	1.08	0.005	0.002	3.05	0.008	0.003	3.27	0.006	0.004	1.62	0.007	0.002	3.43
y2003	0.002	0.001	3.59	0.003	0.001	3.78	0.005	0.002	2.70	0.004	0.002	1.72	0.003	0.003	1.01	0.003	0.002	1.80
y2004	0.001	0.001	1.37	0.002	0.001	2.00	0.003	0.002	2.03	0.003	0.002	1.46	0.001	0.003	0.34	0.002	0.001	1.64
y2005	0.000	0.001	-0.73	0.000	0.001	0.48	0.000	0.001	0.10	0.001	0.002	0.27	0.004	0.003	1.25	0.001	0.002	0.86
y2006	-0.001	0.001	-0.98	0.000	0.001	0.12	0.000	0.001	-0.35	0.001	0.002	0.83	0.001	0.003	0.31	0.002	0.001	1.19
y2007	0.000	0.001	-0.62	0.000	0.001	0.25	0.000	0.001	0.18	0.000	0.002	-0.19	0.005	0.003	1.58	0.001	0.001	0.80
y2008	-0.002	0.001	-3.47	-0.002	0.001	-2.05	-0.002	0.001	-1.56	-0.003	0.002	-1.85	0.004	0.003	1.18	-0.002	0.002	-1.09
y2009		Omitted			Omitted			Omitted			Omitted			Omitted			Omitted	
y2010	-0.005	0.001	-8.78	-0.005	0.001	-6.71	-0.006	0.001	-4.15	-0.009	0.003	-3.49	-0.002	0.003	-0.73	-0.008	0.002	-3.25
y2011	-0.007	0.001	-11.50	-0.007	0.001	-9.01	-0.008	0.002	-5.11	-0.011	0.003	-3.99	-0.007	0.004	-1.64	-0.010	0.002	-4.11
y2012	-0.006	0.001	-8.59	-0.005	0.001	-6.47	-0.007	0.002	-4.26	-0.010	0.003	-3.92	-0.007	0.003	-2.27	-0.009	0.002	-3.99
y2013	-0.006	0.001	-9.04	-0.005	0.001	-6.82	-0.008	0.002	-4.41	-0.010	0.003	-3.72	-0.004	0.004	-1.03	-0.009	0.002	-3.80
y2014	-0.007	0.001	-11.16	-0.007	0.001	-8.82	-0.009	0.002	-4.75	-0.011	0.003	-3.89	-0.004	0.003	-1.25	-0.009	0.002	-3.88
y2015	-0.009	0.001	-14.32	-0.009	0.001	-11.74	-0.011	0.002	-5.72	-0.012	0.003	-4.02	-0.004	0.003	-1.18	-0.010	0.003	-4.04
y2016	-0.009	0.001	-13.49	-0.008	0.001	-10.65	-0.012	0.002	-5.90	-0.012	0.003	-4.05	-0.005	0.004	-1.24	-0.011	0.003	-4.06
y2017	-0.009	0.001	-13.93	-0.009	0.001	-11.03	-0.012	0.002	-5.66	-0.014	0.003	-4.43	-0.005	0.004	-1.34	-0.012	0.003	-4.48
Constant	0.021	0.003	6.14	0.027	0.004	6.52	0.039	0.011	3.43	0.021	0.012	1.76	0.012	0.008	1.51	0.017	0.008	2.27
Observations	184,372			146,977			25,855			9,527			2,013			11,540		
R-squared	0.840			0.835			0.871			0.898			0.781			0.891		

Table 3: Quarterly Models of the Relative Change in Bank Credit Standards on C&I Loans to Small versus Medium- and Large Size Firms (*CSGap*)

Model sample	90:q2-17:q4	Pre-DFA 90:q2-10:q2	90:q2-17:q4	Pre-DFA 90:q2-10:q2
	<u>Model 1</u>	<u>Model 2</u>	<u>Model 3</u>	<u>Model 4</u>
Constant	-0.827 (0.72)	-0.941 (0.60)	-1.501 (1.04)	-1.566 (1.45)
ΔRFM_t	1.311 (1.56)	1.774* (2.02)	1.769+ (1.78)	1.763+ (1.77)
$\Delta AaaTR_t$	-7.913** (3.32)	-8.450** (3.01)	-8.143** (3.40)	-8.129** (3.38)
$\Delta^4 DEL_t$	-2.553* (2.36)	-2.524+ (1.76)	-2.132* (2.09)	-2.137* (2.08)
$DFASB1_t$			4.366** (2.17)	4.500* (2.19)
$DFASB2_t$				0.392 (0.10)
Adjusted R ²	.378	.419	.395	.389
S.E.	5.059	5.238	4.992	5.015
ρ (AR(1))	0.259*	0.291*	0.226*	0.226*
ρ (AR(2))	0.265**	0.308**	0.237**	0.237**
D.W.	2.06	2.06	2.04	2.04
Q(12)	12.24	11.23	9.87	9.87
Q(24)	28.28	22.35	29.90	30.03

Notes: +, *, and ** denote 90%, 95%, and 99% significance levels, respectively. Absolute t-statistics are in parentheses.

Table 4: Quarterly Models of the Birth Rate of Firms (*Birth*)

Sample	93:q2-17:q2	Time Trend 93:q2-17:q2	Simple Reg. 93:q2-17:q2	Tobin's Q 93:q2-17:q2	Reg.Tob.Q 93:q2-17:q2	DFASBI Tob.Q 93:q2-17:q2	DFA Time 93:q2-17:q2	DFA ex.. 93:q2-17:q2
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	3.192** (36.00)	4.203** (25.09)	6.155** (8.36)	2.670** (15.22)	4.999** (5.93)	5.635** (13.94)	3.532** (19.49)	2.882** (30.26)
ΔU_{t-1}	-0.122+ (1.85)	-0.139* (2.38)	-0.257** (4.68)	-0.109+ (1.77)	-0.252** (4.72)	-0.237** (4.93)	-0.219** (4.39)	-0.366** (7.09)
$\Delta AaaTR_{t-1}$	-0.103+ (1.85)	-0.100+ (1.79)	-0.090 (1.61)	-0.133* (2.26)	-0.127* (2.09)	-0.122+ (1.97)	-0.138* (2.32)	-0.133* (2.33)
<i>TobinsQ</i> _{t-3}				0.547** (3.76)	0.310** (3.35)	0.270** (3.11)	0.386** (5.74)	0.446** (5.23)
<i>Time</i> _t		-0.062** (6.00)					-0.040** (3.66)	
<i>RegPerCap</i> _{t-1}			-5.632** (3.82)		-3.933* (2.50)	-5.129* (7.20)		
<i>DFASBI</i> _t			-0.173+ (1.89)		-0.221* (2.53)	-0.164** (3.52)	-0.214** (3.10)	-0.366** (7.09)
<i>DFASB2</i> _t			0.023 (0.22)		-0.103 (0.92)		-0.108 (1.32)	-0.353** (4.96)
Adjusted R ²	.764	.788	.797	.780	.814	.814	.829	.799
S.E.	0.117	0.111	0.109	0.113	0.104	0.104	0.100	0.108
P (AR(1))	0.868**	0.652**	0.402**	0.855**	0.345*	0.443**	0.278**	0.438**
D.W.	2.42	2.21	2.06	2.41	2.03	2.02	2.00	2.09
Q(12)	30.14**	21.58**	12.90	26.16**	10.17	10.83	12.28	12.68
Q(12)	56.94**	44.09**	31.02	48.40**	27.14	27.93	29.16	28.01

Notes: +, *, and ** denote 90%, 95%, and 99% significance levels, respectively. Absolute t-statistics are in parentheses.

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Appendix A: Robustness Checks For Modeling the Small Loan Share

There are four sets of checks done to assess four potential concerns about the small loan share models in Table 1 and Section II. The first is that an uptrend in the general price level could cause substantial migration of loans from being under one million in nominal size to being over one million in nominal size. Unfortunately, detailed data on the distribution of individual loans is not available. Nevertheless, to address this concern, the level of the GDP implicit price deflator (*PGDP*) is added to the cointegrating vector for each of the even-numbered models in Table 2 that contain the cyclical controls which cover the three different size categories of banks. These are numbered Models 2A, 4A, and 6A in Appendix Table A1. The nominal migration concern would imply a negative coefficient on the equilibrium effect of *PGDP* on *SBSH*. However, in each of the models, the coefficient on *PGDP* is either insignificant or has the opposite positive sign, while that on *DFASB* remains significant with the hypothesized negative sign.

The second concern with the models in Table 1 is that an uptrend in the level of per capital nominal GDP could cause substantial migration of loans from being under one million in nominal size to being over one million in nominal size. To address this issue, the level of per capita nominal GDP (*NGDPC*) is added to the same small loan share models. These are numbered Models 2A, 4A, and 6A in Appendix Table A1. The nominal migration concern would imply a negative coefficient on the equilibrium effect of *NGDPC* on *SBSH*. However, in each of the models, the coefficient on *NGDPC* is either insignificant or has the expected negative sign, while that on *DFASB* remains significant with the hypothesized negative sign.

A third concern with the Table 1 results is that they may arise not because of the DFA, but because of a demographic slowdown in the adult population that may start businesses. To address this issue, the growth rate of the prime working age population, defined as being between ages 25

and 54 (*Age2554*) is added to the cointegrating vector of the Table 1 models that include the short-run control variables. These are numbered Models 2C, 4C, and 6C in Appendix Table A2. The demographic slowdown concern would imply a positive coefficient on the equilibrium effect of *Age2554* on *SBSH*. However, *Age2554* is insignificant in every model, while the coefficient on *DFASB* remains significant with the hypothesized negative sign. The poor performance of the demographic variable likely reflects that the slowdown in the growth rate of the working age population began in the 1990s. This is well before the downshift of the small business loan share that occurred following the passage of DFA in 2010 and also before the slowdown in business formation that began in the early 2000s, shortly after the passage of SOX.

A fourth concern with the Table 1 results is that they may arise not because of the DFA, but because of hysteresis effects from the Great Recession. These sorts of effects would reflect long-standing damage to households' ability to start businesses beyond the cyclical variables already in the models. To address this issue and use available data, the quarter end-of-year ratio of household wealth to disposable income (*WIRatio*) from the Financial Accounts of the U.S. is a good candidate variable for two reasons. First, it tracks wealth, which plausibly tracks lasting financial damage to households from asset busts. Second, it is scaled by disposable income which helps abstract from cyclical effects already controlled for in the Table 1 models. *WIRatio* is added to the cointegrating vector of the Table 1 models that include the short-run control variables. These are numbered Models 2D, 4D, and 6D in Appendix Table A2. The hysteresis-wealth effect concern would imply a positive coefficient on the equilibrium effect of *WIRatio* on *SBSH*. In all three models, significant and unique cointegrating vectors were identified. In only one of the three cases (and for the smallest bank category) was the coefficient on *WIRatio* significant with the expected positive long-run effect of *WIRatio* on *SBSH*. In all three cases the DFA dummy

continued to have a negative and significant effect. Hence, the inclusion of the wealth ratio did not overturn the principal finding that the small loan share was negatively affected by DFA over the long-run. This result was also robust to the inclusion of the price level, nominal GDP, and a variable controlling for the aging of the U.S. working-age population.

Appendix Table A1: Annual Models of the Small-Sized Loan Share of C&I Loans

Long-Run Equilibrium: $SBSH_t = \alpha_0 + \alpha_1 DFASB_t + \alpha_2 PGDP_t/NGDPC_t + \varepsilon_t$

Variables	Bank Asset Size Classes					
	All		Large (assets>\$1B)		Small (300M<assets<\$1B)	
Model No.	2A	2B	4A	4B	6A	6B
Constant	0.2652	0.2487	0.1661	0.1952	1.331	0.2447
$DFASB_t$	-0.1135** (6.10)	-0.1080** (8.50)	-0.1157** (6.10)	-0.0997** (8.64)	-0.0360** (8.73)	-0.1472** (9.57)
$PGDP$ (A models)	0.0014	0.00004	0.0008	0.000008	0.0099**	-0.00036*
$NGDPC$ (B models)	(0.02)	(0.44)	(0.97)	(1.32)	(8.03)	(6.14)
unique coint.	Yes*	Yes*	Yes*	Yes ⁺	Yes**	Yes**
vec. # lags	1	1	1	1	2	2
trace no vec.	33.56*	29.80*	31.76*	29.80 ⁺	50.96**	54.61**
trace at least 1	12.87	7.19	11.86	5.80	20.12	15.30
trace at least 2	1.19	0.22	1.15	0.21	1.11	4.25
Short-Run: $\Delta SBSH_t = \beta_0 + \beta_1 EC_{t-1} + \sum \beta_{2i} \Delta SBSH_{t-i} + \sum \beta_{3i} \Delta DFASB_{t-i} + \sum \beta_{4i} \Delta PGDP/NGDPC_{t-i} + \beta_5 X_{t-1} + \mu_t$						
EC_{t-1} , 'adjustment speed'	-0.251** (2.86)	-0.257* (2.54)	-0.218* (2.53)	-0.253* (2.42)	-1.208** (5.30)	-0.355* (2.52)
$\Delta SBSH_{t-1}$	0.512** (4.02)	0.515** (3.88)	0.523** (3.84)	0.522** (3.78)	0.299 ⁺ (1.88)	-0.073 (0.36)
$\Delta PGDP$ (A models)	0.0004	-0.00001**	-0.0012	-0.00001	-0.016 ⁺	0.00005
$\Delta NGDPC$ (B models)	(0.08)	(3.37)	(0.36)	(0.48)	(1.80)	(1.02)
$\Delta DFASB_{t-1}$	-0.014 (0.87)	-0.014 (0.82)	0.015 (0.96)	-0.014 (0.86)	0.007** (2.78)	0.003 (0.15)
$BaaTR10_{t-1}$	0.010* (2.23)	0.008 ⁺ (1.76)	-0.008 ⁺ (1.86)	-0.006 (1.61)	-0.009** (4.13)	-0.012** (2.69)
$\Delta^2 LEI_{t-1}$ $x100$	-0.176** (5.53)	-0.159** (4.09)	-0.165** (5.21)	-0.150** (3.92)	0.000 (1.09)	0.000* (1.08)
$D2008_{t-1}$	-0.024** (2.63)	-0.026** (3.09)	-0.024** (2.72)	-0.025** (3.16)	-0.017** (4.28)	-0.026** (3.53)
Constant	-0.022 (1.94)	0.016 (1.33)	0.016 (1.51)	0.0132 (1.13)	0.001 (0.13)	0.015 (0.17)
Adj. R ²	0.796	0.799	0.783	0.798	0.884	0.577
S.E.x100	0.770	0.765	0.751	0.725	0.304	0.581
VEC Auto (1)	8.45	11.64	8.41	12.13	8.65	3.76
VEC Auto (2)	10.48	14.55	10.32	15.64	24.57**	10.36

Estimated using data spanning 1993-2016 or 1993-2017. Notes: (i) Absolute t-statistics in parentheses. ** (*): significant at the 99% (95%) confidence level. (ii) Long-run: Maximum likelihood estimates of the long-run equilibrium relationship using a three-equation system with at most one cointegrating vector. (iii) Short-run: OLS estimates of speed of adjustment and short-run dynamics using the estimated equilibrium correction terms in (ii). (iv) First difference terms of elements in the long-run cointegrating vector after t-1 omitted to conserve space. (v) Lag lengths chosen to minimize the AIC criterion.

Appendix Table A2: Annual Models of the Small-Sized Loan Share of C&I Loans

Long-Run Equilibrium: $SBSH_t = \alpha_0 + \alpha_1 DFASB_t + \alpha_2 Age2554_t/WIRatio_t + \varepsilon_t$

Variables	Bank Asset Size Classes					
	All		Large (assets>\$1B)		Small (300M<assets<\$1B)	
Model No.	2C	2D	4C	4D	6C	6D
Constant	0.2557	0.1953	0.2391	0.1953	1.1981	1.269
$DFASB_t$	-0.1017** (18.22)	-0.0885** (13.04)	-0.0969** (8.48)	-0.0885** (13.04)	-0.0733** (10.40)	-0.1237** (7.90)
$Age2554$ (C models)	0.989	0.0049	0.1412	0.0059	-0.2830	0.0723**
$WIRatio$ (D models)	(0.62)	(1.03)	(0.83)	(1.03)	(0.49)	(6.38)
unique coint.	Yes**	Yes**	Yes*	Yes**	No	Yes**
vec. # lags	2	1	2	1	1	1
trace no vec.	39.34**	46.03**	33.66**	45.43**	67.09**	65.85**
trace at least 1	13.23	15.04	10.77	14.25	26.01*	21.21
trace at least 1	1.18	0.83	1.30	1.04	5.49	4.17

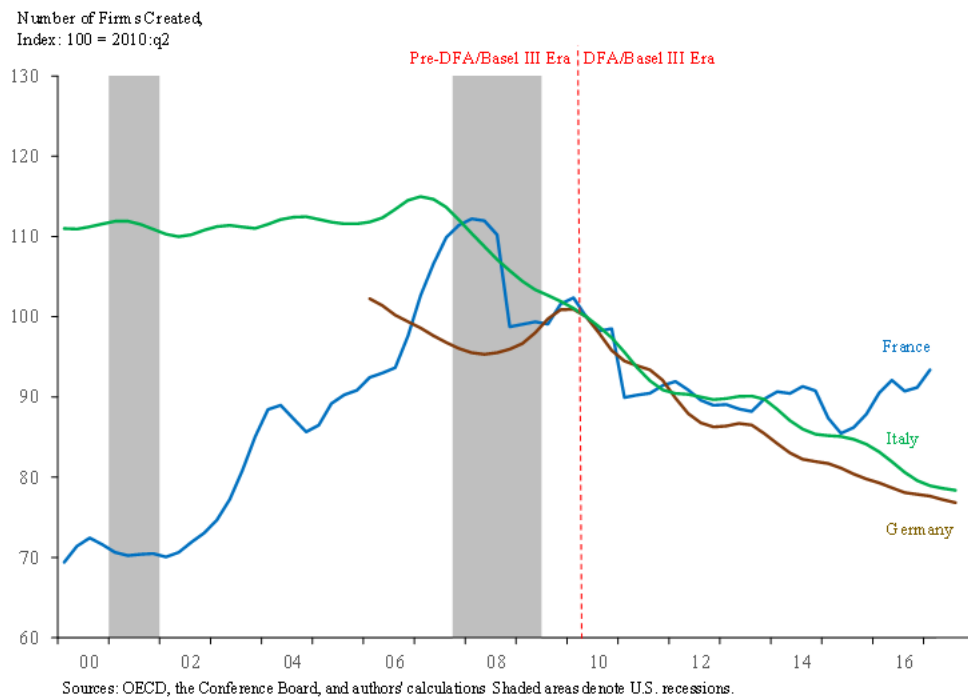
Short-Run: $\Delta SBSH_t = \beta_0 + \beta_1 EC_{t-1} + \sum \beta_{2i} \Delta SBSH_{t-i} + \sum \beta_{3i} \Delta DFASB_{t-i} + \sum \beta_{4i} \Delta PGDP/WIRatio_{t-i} + \beta_5 X_{t-1} + \mu_t$

EC_{t-1}	-0.402** (4.13)	-0.250** (2.73)	-0.383** (3.50)	-0.249* (2.59)	-0.149 (1.51)	-0.079+ (1.65)
'adjustment speed'						
$\Delta SBSH_{t-1}$	0.679** (5.53)	0.538** (5.33)	0.823** (6.30)	0.554** (5.24)	0.011 (0.05)	-0.029 (0.13)
$\Delta Age2554$ (A models)	0.148	-0.008+	0.828**	-0.008*	-0.099	0.004
$\Delta WIRatio$ (B models)	(0.49)	(1.75)	(2.68)	(2.05)	(0.37)	(0.83)
$\Delta DFASB_{t-1}$	-0.018 (1.22)	-0.021+ (1.47)	-0.020 (1.29)	-0.018 (1.26)	-0.005 (0.41)	-0.010 (0.83)
$BaaTR10_{t-1}$	0.011** (2.90)	0.009* (2.56)	0.006+ (1.79)	0.009 (2.49)	-0.005 (1.52)	-0.008** (2.07)
$\Delta^2 LEI_{t-1}$	-0.162** (5.61)	-0.167** (6.16)	-0.151** (5.07)	-0.166** (6.14)	0.000 (0.16)	0.000 (0.79)
$x100$						
$D2008_{t-1}$	-0.023** (3.27)	-0.026** (3.61)	-0.026** (3.66)	-0.026** (3.61)	-0.031** (3.94)	-0.031** (4.02)
Constant	-0.029** (2.91)	-0.021* (2.38)	0.015+ (1.73)	-0.021* (2.29)	0.002 (0.26)	0.010 (1.12)
Adj. R ²	0.870	0.853	0.853	0.841	0.445	0.468
S.E.x100	0.628	0.655	0.631	0.643	0.659	0.645
VEC Auto (1)	8.62	10.93	9.82	9.76	8.55	10.73
VEC Auto (2)	10.31	6.94	7.89	6.83	6.33	9.04

Estimated using data spanning 1993-2016 or 1993-2017. Notes: (i) Absolute t-statistics in parentheses. ** (*): significant at the 99% (95%) confidence level. (ii) Long-run: Maximum likelihood estimates of the long-run equilibrium relationship using a three-equation system with at most one cointegrating vector. (iii) Short-run: OLS estimates of speed of adjustment and short-run dynamics using the estimated equilibrium correction terms in (ii). (iv) First difference terms of elements in the long-run cointegrating vector after t-1 omitted to conserve space. (v) Lag lengths chosen to minimize the AIC criterion.

Appendix B: Business Formation Weak in Major European Countries Since Basel III Was Announced

Because the DFA is in accord with the Basel III agreement,¹⁷ business formation in other advanced economies could also have been affected by the announcement of Basel III in 2010. As illustrated in Appendix Figure B1, this possibility is consistent with downward inflection points or continued declines in indexes of total firm formation¹⁸ available for three of the five largest European economies (France, Italy, and Germany). Thus, our U.S. findings may have implications for the impact of Basel III on SME lending and business formation in other nations, with appropriate qualifications for cross-national differences in economic structure and regulation.¹⁹



Appendix Figure B1: New Business Formation Falls in Three Major European Countries after Dodd-Frank and Basel III Are Announced. Source: OECD.

¹⁷ Basel III was announced three months after DFA was passed in July 2010, but was well anticipated earlier in 2010.

¹⁸ Indexes are of newly formed unincorporated firms but not scaled by the number of existing firms as for the U.S.

¹⁹ Our time series study focuses on U.S. effects of Basel III because long and detailed enough data on economies in Europe and Japan are not available. Because these other countries have more bank-centric financial systems than the U.S., Basel III effects could be more pronounced than for the U.S. However, because business entry rates are generally much higher in the U.S. the macroeconomic impact of Basel III on SMEs may be weaker than in the U.S.