Internet Appendix for Asset Allocation in Bankruptcy

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This appendix contains additional descriptions, results, and robustness tests to supplement the analyses in the paper. Section A below provides a full description of the analysis in each table. Section B provides the formal derivation of the search model briefly described in Section II in the paper. Section C describes the matching process of the bankruptcy filings to the census data, and sample selection. Finally, Section D describes the address matching algorithm and the construction of the geographical linkages.

Table A.1
Direct-to-Ch. 7 Summary Statistics

This table displays average plant- and firm-level characteristics of firms that file for and remain in Ch. 11, that file for Ch. 11 but convert to Ch. 7, and that file directly for Chapter 7 bankruptcy. Columns 1 and 2 are repeated from Panel A of Table 1 in the main text of the paper.

	Remain in Ch. 11	Convert to Ch. 7	Direct to Ch. 7
Plant-level characteristics			
Employment	38.0	26.9	15.1
Total plants	105,000	24,000	39,000
Firm-level characteristics			
No. Plants	6.5	2.2	1.4
Employment	245.4	57.9	20.4
Payroll (000s)	6,819.0	1,146.3	338.3
Payroll/Employee (000s)	26.0	20.2	13.8
Age	10.7	8.9	7.8
Number of firms	17,000	11,000	29,000

Table A.2
Alternative Instruments

This table reports results using alternative instruments. Panel A shows first stage regression results identical to Column 3 of Table 3. In the first column, we use the share of cases assigned to the judge in the past 5 years that have been converted to Chapter 7 as the instrument. In the second column, we include a comprehensive set of 559 individual judge fixed effects. In Panel B, we present the main 2SLS results using the share of cases converted in the past 5 years as the instrument, as compared to the leave-one-out instrument we use in the paper that uses the share of all cases. Panel C shows that judge leniency is constant over time. The first two columns regress the share of cases converted in the past 5 years on the share of cases converted over the full sample. Columns 3-7 regress the share of cases converted in the 1st half of a judge's tenure on the share converted in the 2nd half, for judges with varying amounts of cases. Dependent variables and controls are defined identically to Table 6. Standard errors, clustered at the division-by-year level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: First Stage with Alternative Instruments

Dependent variable:	Converted to Chapter 7	
	(1)	(2)
Share of cases in past 5 years converted	0.304***	
	(0.028)	
Judge fixed effects		Yes***
Ln(employees at plant)	0.016***	0.009***
	(0.003)	(0.003)
Plant age (years)	-0.005***	-0.002***
	(0.000)	(0.000)
Ln(tot. employees at firm)	-0.033***	-0.037***
	(0.004)	(0.007)
Ln(no. of plants at firm)	-0.022***	-0.011
	(0.006)	(0.011)
Part of a group filing	-0.087***	-0.061*
	(0.011)	(0.037)
2-digit NAICS Fixed Effects	Yes	Yes
Division-year Fixed Effects	Yes	Yes
Observations	129,000	129,000
Adj. R-squared	0.172	0.465
F-stat for instrument	116.6	

Table A.2
Alternative Instruments (cont.)

Panel B: Second Stage with Alternative Instrument

Dependent variable:	Continues		Occupied		Ln(Avg. Employment)		Ln(Avg. Total Wages)	
Instrument:	Past cases	All cases	Past cases	All cases	Past cases	All cases	Past cases	All cases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Liquidation	-0.368***	-0.324***	-0.135*	-0.174**	-0.555***	-0.416*	-0.819**	-0.921**
	(0.051)	(0.061)	(0.071)	(0.079)	(0.212)	(0.217)	(0.369)	(0.368)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,000	129,000	129,000	129,000	129,000	129,000	129,000	129,000
Adjusted R-squared	0.146	0.152	0.039	0.039	0.217	0.214	0.231	0.232

Panel C: Judge Leniency Over Time

Dependent variable:	Share of all cases converted		Share of cases converted 2nd half				
			All judges	> 10 cases	> 20 cases	> 50 cases	> 100 cases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of cases in past 5 years converted	1.052***	1.055***					
	(0.006)	(0.006)					
Share of cases converted 1st half			0.742***	0.823***	0.859***	0.905***	0.982***
			(0.022)	(0.018)	(0.019)	(0.022)	(0.026)
2-digit NAICS Fixed Effects	No	Yes	No	No	No	No	No
Division-year Fixed Effects	No	Yes	No	No	No	No	No
Firm and Plant controls	No	Yes					
Observations	129,000	129,000					
Number of judges	530	530	530	440	320	200	80
Percent of sample			1	0.954	0.871	0.716	0.424

Table A.3
Effect of Forum Shopping on First Stage

This table displays the first stage regression for sets of firms that can and cannot forum shop. Column 1 limits the sample to firms with establishments in a single county (which cannot forum shop), while column 2 limits to firms in multiple counties (which may be able to forum shop). Similarly, Columns 3 and 4 split the sample by firms located in sinlge or multiple states. All controls are identical to Table 3. Standard errors, clustered at the division-by-year level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Converted to Chapter 7			
Sample:	Single-county	Multi-county	Single-state	Multi-state
	(1)	(2)	(3)	(4)
Share of other cases converted	0.596***	0.630***	0.604***	0.429***
	(0.061)	(0.130)	(0.059)	(0.156)
Control Variables	Yes	Yes	Yes	Yes
2-digit NAICS Fixed Effects	Yes	Yes	Yes	Yes
Division-year Fixed Effects	Yes	Yes	Yes	Yes
Observations	26,000	103,000	32,000	97,000
Adj. R-squared	0.106	0.497	0.120	0.541

Table A.4
Reduced Form Regressions

This table reports reduced-form regressions in which the instrument, *share converted*, is entered directly as an independent variable, rather than the 2SLS procedure used in the main text. Dependent variables and control variables are identical to those in Panel A of Table 6. Standard errors, clustered at the division-by-year level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Continues (1)	Occupied (2)	Ln(Avg. Employment) (3)	Ln(Avg. Total Wages) (4)
Share converted	-0.188***	-0.101**	-0.241*	-0.544**
	(0.039)	(0.046)	(0.130)	(0.227)
Control Variables	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes
Observations	129,000	129,000	129,000	129,000
Adjusted R-squared	0.114	0.110	0.264	0.284

Table A.5
Exclusion Restriction Tests

This table reports tests of the exclusion restriction condition. Reduced-form regression results are presented where the instrument, *share converted*, is entered directly as an independent variable. We run these regressions separately on the sub-sample of firms that remain in Chapter 11 reorganization and on the sub-sample that is converted to Chapter 7 liquidation. Dependent variables and control variables are identical to those in Panel A of Table 6, excluding $Ln.Avg.TotalWages$ for brevity (for results are similar). In Column 7, we also show that the instrument is unrelated to the propensity for reorganized firms to re-file for bankruptcy. Standard errors, clustered at the division-by-year level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Continues		Occupied		Ln(Avg. Employment)		Re-filing
Sample:	Reorganized (1)	Liquidated (2)	Reorganized (3)	Liquidated (4)	Reorganized (5)	Liquidated (6)	Reorganized (7)
Share converted	-0.050	-0.016	-0.063	-0.001	-0.113	0.296	-0.001
	(0.062)	(0.019)	(0.061)	(0.082)	(0.168)	(0.214)	(0.042)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,000	24,000	105,000	24,000	105,000	24,000	105,000
Adjusted R-squared	0.186	0.190	0.151	0.208	0.373	0.259	0.1509

Table A.6

Plant Outcomes with Division Fixed Effects

This table displays the main second stage results when we include bankruptcy division fixed effects instead of division-by-year fixed effects, and cluster standard errors at the divsion level as well. Specifications are otherwise identical to Table 6 in the main text. Standard errors, clustered at the division level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Continues (1)	Occupied (2)	Ln(Avg. Employment) (3)
Liquidation	-0.2579*** (0.046)	-0.1930*** (0.049)	-0.4800*** (0.137)
Control Variables	Yes	Yes	Yes
Division FE	Yes	Yes	Yes
Observations	129,000	129,000	129,000
Adjusted R-squared	0.148	0.0363	0.217

Table A.7

Dynamics of Utilization

This table shows how utilization is affected by liquidation over time. The table shows 2SLS estimates of the effect of liquidation on utilization 1, 3, and 5 years after the bankruptcy filing. Dependent variables are defined as in Table 6. We also display the effect on total payrolls in addition to number of employees. Control variables are identical to those in Panel A of Table 6. Standard errors, clustered at the division-by-year level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:		Occupied			Ln(Avg. Employment)			Ln(Avg. Total Wages)	
Years post filing:	+1	+3	+5	+1	+3	+5	+1	+3	+5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidation	-0.237***	-0.192**	-0.174**	-0.479**	-0.419*	-0.416*	-1.448***	-1.031***	-0.921**
	(0.075)	(0.078)	(0.079)	(0.236)	(0.222)	(0.217)	(0.395)	(0.365)	(0.368)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,000	129,000	129,000	129,000	129,000	129,000	129,000	129,000	129,000

Table A.8
Robustness of Results to Matching Algorithm

This table repeats the main analysis from Panel A of Table 6 on three sub-samples of plants to demonstrate that the results are not affected by the co-location of establishments. Panel A limits the sample only to establishments with unique addresses in the year prior to the bankruptcy. In Panel B, we remove from the sample any plant that matched to multiple new establishments after closing. Panel C removes locations that are likely to be shopping centers or office buildings by dropping all locations that have >5 establishments. Dependent variables and controls are identical to those in Panel A of Table 6. Standard errors, clustered at the division-by-year level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Only Single-unit Locations

Dependent variable:	Occupied (1)	Ln(Avg. Employment) (2)	Ln(Avg. Total Wages) (3)
Liquidation	-0.309*** (0.112)	-1.045*** (0.282)	-2.044*** (0.524)
Control Variables	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes
Observations	68,000	68,000	68,000

Panel B: No Multiple-matched Locations

Dependent variable:	Occupied (1)	Ln(Avg. Employment) (2)	Ln(Avg. Total Wages) (3)
Liquidation	-0.373*** (0.093)	-1.062*** (0.237)	-2.059*** (0.427)
Control Variables	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes
Observations	97,000	97,000	97,000

Panel C: No Shopping Centers or Office Buildings

Dependent variable:	Occupied (1)	Ln(Avg. Employment) (2)	Ln(Avg. Total Wages) (3)
Liquidation	-0.282*** (0.089)	-0.770*** (0.210)	-1.415*** (0.383)
Control Variables	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes
Observations	107,000	107,000	107,000

Table A.9

Heterogeneity Measures Summary Statistics By Industry

This table reports the average and standard deviation of our two main measures of local market search costs by industry. *Market thickness* is a measure of the market share of firms in the same or similar industries in the county, and is defined in the text. *Share of small business loans* is the percentage of loans in the county that are given to small businesses.

	Market Thickness		Share of small business loans	
	Average	SD	Average	SD
Agriculture, Mining and Construction	0.06	0.02	0.45	0.12
Manufacturing	0.06	0.03	0.45	0.12
Transportation, Utilities, and Warehousing	0.05	0.02	0.44	0.12
Wholesale & Retail Trade	0.06	0.02	0.45	0.11
Services	0.06	0.02	0.43	0.11
Accomodation, Food, and Entertainment	0.08	0.04	0.45	0.11
Other	0.08	0.04	0.45	0.12

Table A.10

Heterogeneity Measures Correlation Matrix

This table reports pairwise correlations between 7 measures of market conditions used to test for heterogeneity in the main results. There are 2 measures of the number of potential buyers in the county. *Market thickness* is a measure of the market share of firms in the same or similar industries in the county, and is defined in the text. *Real estate transactions per capita* is the total number of commercial real estate transactions reported in CoreLogic in a county in the year of the bankruptcy filing, scaled by the total population of the county. There are 3 measures of access to finance. *Share of small business loans* is the percentage of loans in the county that are given to small businesses. We present this metric both on a number- and value-weighted basis. *Small bank market share* is the share of bank deposits in a county held by commercial banks below the 95th percentile in the overall size distribution in the bankruptcy filing year. Finally, there are 2 measures of 3-year employment growth. Our main measure is the growth rate of employment in the entire county over 3 years prior to the bankruptcy filing. The second is the growth rate of employment in the county in the same 2-digit NAICS as the bankrupt firm over 3 years prior to bankruptcy. Correlations are measured over the full sample of 129,000 plants, except for measures (3) and (4) for which data is available only beginning in 1996.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of potential buyers							
(1) Market thickness	1.00						
(2) Real estate transactions per capita	0.07	1.00					
Access to finance							
(3) Share of small business loans (number-weighted)	0.08	-0.11	1.00				
(4) Share of small business loans (value-weighted)	0.10	-0.03	0.53	1.00			
(5) Small bank market share	0.09	-0.13	0.27	0.47	1.00		
Employment growth							
(6) 3-year employment growth rate for county	0.04	0.14	0.11	0.00	0.03	1.00	
(7) 3-year employment growth rate for industry-county	0.01	0.02	0.02	0.02	0.02	0.09	1.00

Table A.11
Alternative Heterogeneity Measures

This table reports results identical to Table 7 but using alternative measures of market charactertistics to split the sample. Panel A uses *real estate transactions per capita*, defined as the number of commercial real estate transactions reported in CoreLogic in a county in the year of the bankruptcy filing, scaled by population. Panel B uses the value-weighted (instead of number-weighted) share of small business loans in the county. In Panel C, the sample is split by s*mall bank market share,* defined as the share of bank deposits in a county held by commercial banks below the 95th percentile in the overall size distribution in the bankruptcy filing year. Panel D splits the sample by the 3-year growth of employment in the county in the same 2-digit NAICS as the bankrupt firm over 3 years prior to bankruptcy. Dependent variables are measured 5 years after bankruptcy and are defined identically as Panel A of Table 6. For brevity, we omit regressions with ln(*avg. total wages*) as the dependent variable; results for this measure show a similar pattern. All regressions are estimated by 2SLS and contain the full set of control variables in Column 3 of Table 3, including division-by-year and industry fixed effects. Standard errors, clustered by division-year company, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Real Estate Transactions Per Capita

Dependent variable:	Continues		Occupied		Ln(Avg. Employment)	
Above or below median:	Above	Below	Above	Below	Above	Below
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation	-0.390***	-0.276***	-0.110	-0.196**	-0.080	-0.538**
	(0.112)	(0.069)	(0.150)	(0.090)	(0.428)	(0.222)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,000	65,000	64,000	65,000	64,000	65,000

Panel B: Value-weighted Share of Small Business Loans

Dependent variable:	Continues		Occupied		Ln(Avg. Employment)	
Above or below median:	Above	Below	Above	Below	Above	Below
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation	-0.317**	-0.300***	0.002	-0.261**	-0.462	-0.718**
	(0.152)	(0.080)	(0.192)	(0.111)	(0.474)	(0.291)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,000	49,000	50,000	49,000	50,000	49,000

Panel C: Market Share of Small Banks

Dependent variable:	Continues		Occupied		Ln(Avg. Employment)	
Above or below median:	Above	Below	Above	Below	Above	Below
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation	-0.363***	-0.293***	-0.211	-0.131	0.085	-0.460**
	(0.128)	(0.064)	(0.170)	(0.088)	(0.472)	(0.233)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,000	65,000	64,000	65,000	64,000	65,000

Table A.11
Alternative Heterogeneity Measures (cont.)

Panel D: 3-year Employment Growth in County

Dependent variable:	Continues		Occupied		Ln(Avg. Employment)	
Sample:	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation	-0.412***	-0.262***	-0.126	-0.211**	-0.120	-0.644**
	(0.094)	(0.074)	(0.133)	(0.093)	(0.360)	(0.254)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,000	64,000	65,000	64,000	65,000	64,000
Adjusted R-squared	0.098	0.133	0.010	0.013	0.160	0.208

Panel E: 3-year Employment Growth in Industry-County

Dependent variable:	Continues		Occupied		Ln(Avg. Employment)	
Sample:	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation	-0.408***	-0.267***	-0.118	-0.218**	-0.316	-0.497*
	(0.082)	(0.090)	(0.119)	(0.099)	(0.340)	(0.263)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,000	65,000	64,000	65,000	64,000	65,000
Adjusted R-squared	0.118	0.124	0.009	0.005	0.180	0.195

Table A.12
Liquidation and Productivity

This table shows the effect of liquidation on total factor productivity (TFP) for manufacturing plants. The dependent variable is the log of average TFP over 5 years after bankruptcy at a given location, regardless of the plant occupant. TFP is not measured for two sets of plants: those that transition out of manufacturing and those that are vacant. We assume that plants that transition out of manufacturing have the median TFP in that year, but results are not sensitive to this assumption. Meanwhile, each set of columns shows a different assumption for the TFP of vacant locations. In the first two columns, we assume that vacant locations have *ln(TFP)*=0, and in the remaining columns we set TFP to the 10th and 20th percentiles of the full TFP distribution. Both OLS and instrumented (2SLS) estimates are shown. All regressions contain the full set of control variables in Column 3 of Table 3, including division-by-year and industry fixed effects. Standard errors, clustered at the division-by-year level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Ln(Average TFP)					
Vacant-plant TFP set to:	Zero		10th percentile		20th percentile	
Model:	OLS	IV-2SLS	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation	-0.388***	-0.538**	-0.181***	-0.220*	-0.132***	-0.145
	(0.048)	(0.227)	(0.026)	(0.128)	(0.022)	(0.111)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Div x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,500	2,500	2,500	2,500	2,500	2,500
R-squared	0.416	0.153	0.392	0.160	0.379	0.153
1st stage F-stat		13.08		13.08		13.08

A Robustness and Additional Results

This section describes a set of additional tables that test the robustness of our results to alternative measures and different samples. We also present auxiliary results that support the main analysis in the paper.

Table A.1 displays average characteristics of firms that file for and remain in Chapter 11, that file for Chapter 11 but convert to Chapter 7, and that file directly for Chapter 7. Our analysis uses only firms in the first two categories, but this table provides information on the relative size of firms that do not even attempt to reorganize. According to U.S. Courts filing statistics, direct-to-Ch. 7 filings compose 72% of all non-farm business bankruptcies. Thus, while direct-to-Ch. 7 firms on average occupy only 1.4 locations (as compared to 4.7 for the average Ch. 11 filer - see Table 1) and are thus 30% of the size of Ch. 11 filers, in aggregate they hold about 43% of the total commercial real estate that passes through bankruptcy. To obtain data on direct-to-Ch. 7 filers, we obtained the names of businesses that filed for Chapter 7 from LexisNexis and matched those to firms in the LBD.[1]

In Table A.2, we report first and second stage results using alternative instruments. One might be concerned that a judge's preferences change over time and therefore using the share of all cases converted might not accurately represent his current views. Accordingly, Panel A shows that our first stage results are robust to using the share of cases converted in the previous 5 years as the instrument. Further, column 2 of this panel shows that a comprehensive set of judge fixed effects are highly significant, and that including these fixed effects does not appreciably change the coefficient estimates of other control variables. In Panel B, we report the 2SLS results using the share of cases converted in the previous 5 years as the instrument, focusing on the four main dependent variables discussed in the main results. For ease of comparison, we also repeat the estimates from the main results using the share of all cases converted. Lastly, Panel C presents evidence that judge preferences are quite stable over time. In the first two columns we regress the main instrument in the paper that uses all cases on the alternative instrument which uses only cases in the previous 5 years. We find that the coefficient is close to one and highly significant, even when adding all controls. In columns 3-7, we explore the correlation of judge leniency in the first half of the sample and the second half. To do so, we take all cases assigned to a judge and divide them into two equal-sized subsamples by time. We then calculate the share of cases converted by the judge in each half of his tensure, and regress the conversion rate in the 1st half on that of the 2nd half. Thus, in these regressions each observation represents a single judge. The judge rulings in the first half very strongly predict his subsequent rulings in the second half of the analysis. This is particularly true as we rely on judges that have more cases (right-most columns), and thus we can estimate their leniency in both halves more accurately. As we limit to judges with more cases, the correlation is increasing and converging to 1. For example, limiting to judges with at least 100 cases (50 in each subsample), we find that the coefficient is 0.982. This is also consistent with Dobbie and Song (2015), who find that judge biases (in Ch. 13 personal bankruptcy cases) are very consistent over time.

One possible concern with our empirical strategy is that some firms can choose where to file for bankruptcy if they have multiple business locations or are incorporated in a different state than their headquarters. Because we include division-by-year fixed effects in all specifications, we only compare firms that enter the same court, i.e. after any forum selection has taken place, and therefore this type of selection does not affect our resutls. Nevertheless, in Table A.3 we show that the first stage is robust to limiting to firms that can and cannot forum shop. Specifically, in columns (1) and (2) we divide our sample into firms with all plants in a single county (which cannot forum shop because all business locations reside in the same bankruptcy district) and multi-county firms (which may be able to forum shop). Similarly, in columns (3) and (4) we divide the sample into firms with locations in one state or multiple states. In all cases, the first stage regression is highly significant and largely unchanged from the overall specification.

Table A.4 shows reduced form results, where we regress our main dependent variables of interest directly on the preferred instrument, namely the share of all other Chapter 11 cases that a judge converted to Chapter 7. Consistent with our story, and similarly to what we show in Table 6, we find that a higher *share of other cases converted* is associated with lower asset utilization for all three measures. Coefficients from these reduced form regressions are presented graphically for each year after bankruptcy in Figure 5 in the main text.

While we cannot test the exclusion restriction directly, indirect tests support the identifying assumption,

[1] EIN numbers were not available for these firms, so we match by name and state instead.

as also discussed in the main text. We report the results of these tests in Table A.5. We run a set of reduced-form regressions which directly relate our preferred instrument, *share of other cases converted*, to plant outcomes. In particular, we do so by limiting the samples to either firms that stay in Chapter 11, or to firms that are converted to Chapter 7. Since we find a strong relationship between the instrument and the plant outcomes on the full sample, we should expect to find similar results separately on the Chapter 11 and Chapter 7 sub-samples *if* judge attributes are such that the exclusion restriction condition is violated (i.e. if our instrument affects plant outcomes in other ways that are different from the conversion of a case to Chapter 7). Reassuringly, this is not the case, as it is clear from the statistically insignificant coefficients of Columns 1-6. Further, we also find that within Chapter 11 reorganization, the instrument is uncorrelated with bankruptcy refiling rates, a proxy for bankruptcy resolution success.

In our main specifications we always include bankruptcy division-by-year fixed effects to ensure that we are comparing firms that file in the same bankruptcy court in the same year to each other. This is necessary because random assignment of judges occurs within a bankruptcy district. Because the composition of bankruptcy judges in a district evolves over time (due to the appointment and retirement of judges), we use division-by-year fixed effects rather than simple division fixed effects. However, in Table A.6 we show that our results are essentially identical when we include only division fixed effects. In fact, because these specifications have far fewer fixed effects, this change reduces the standard errors of our estimates, making all coefficients significant at the 1% level.

In the main text, Figure 5 displays how the effect of liquidation evolves over time. This figure relies on reduced form regressions. In Table A.7 we display dynamic 2SLS results to show that the effects are consistent whether using reduced form or 2SLS estimation. The table displays coefficient estimates based on utilization measured 1, 3, and 5 years after bankruptcy. We also provide these estimates to show that our results are similar when measuring utilization by total wages instead of total employees.

Given the inherent imprecision of address matching, in Table A.8 we report our main results when limiting the sample to plants for which we are more confident of the address match and, hence, utilization measurement. The goal is to show that the results are not affected by the co-location of establishments. Panel A limits the sample only to establishments with unique addresses in the year prior to the bankruptcy. In Panel B, we remove from the sample any plant that matched to multiple new establishments after closing. Panel C removes locations that are likely to be shopping centers or office buildings by dropping all locations that have >5 establishments. All the results are essentially unchanged and, if anything, larger in magnitude.

Our main analysis emphasizes the role played by local market characteristics in determining the impact of different bankruptcy regimes on plant outcomes. In Table A.9 we show that our two main measures of local market search costs, market thickness and access to small business capital, do not vary much by industry. Rather, the mean values of these measures are very similar across all industries in our sample, and standard deviations within industry are relatively large. This means that most of the variation we capture in these measures is within-industry, rather than across industries.

Because the heterogeneity results play a key role in the paper, it is important to show their robustness. We therefore construct and adopt a set of alternative measures as well. As an alternative measure to market thickness, we rely on the Core Logic dataset to create *real estate transactions per capita*. This measure is computed as the total number of commercial real estate transactions reported in CoreLogic in a county in the year of the bankruptcy filing, scaled by the total population of the county, and is meant to capture the number of potential buyers of real estate assets. This captures market thickness in an alternative way by measuring the liquidity in the commercial real estate market. We then move to our main measure of access to finance, namely *share of small business loans*, and complement it with two additional measures. The first is the value-weighted version of *share of small business loans*. The second, *small bank market share*, is computed using the FDIC's Summary of Deposits data and is defined as the share of bank deposits in a county held by commercial banks below the 95th percentile in the overall bank size distribution in the bankruptcy filing year. This variable stems from the idea that small, local banks are the principle providers of capital for small firms (Petersen and Rajan (1994)). Banks below the 95th percentile hold about 25% of all deposits and constitute about 40% of all branches in the U.S. during our sample period. Further, small banks tend to have deposits concentrated in local markets. Large banks have branches in over 15 different counties on average, while small banks are present in only 1.7 counties. Overall, we therefore work with 7 measures of market conditions. Table A.10 reports the pairwise correlation matrix of these 7 measures. As expected, there is positive correlation within categories (e.g. measures of access to finance are correlated with each other). However, most of the correlations tend to be low, displaying a substantial variation that each measure is independently responsible for when looking at local market conditions. To conclude, in Table A.11 we report results identical to Table 7 but using the five alternative measures of market charactertistics to split the sample. The results show a similar pattern to what we find using the main heterogeneity measures, thus providing further evidence for the results discussed in the main text.

In Table A.11 we also show that we split regions by growth rates we find similar results to market thickness and access to capital reported in the main paper. Specifically, for each county we calculate the employment growth rate over the three years prior to the bankruptcy filing, and then divide counties into above- and below-median growth counties. In Panel D of Table A.11 we show that liquidation reduces asset utilization especially in low-growth counties. These results suggest that reallocation is especially difficult when an area is in decline. In Panel E we show that similar results hold when splitting employment growth by both the same 2-digit NAICS as the bankrupt firm and county over the 3 years prior to the bankruptcy.

Our main results focus on measures of utilization as outcome variables. However, since utilization is not a direct measure of efficiency it is difficult to make a definitive judgment on the effiiciency of either bankruptcy regime. To shed some light on this issue, in Table A.12 we focus on liquidation's impact on total factor productivity (TFP) of manufacturing plants. This analysis is limited to 2,500 manufacturing plants which are in the Annual Survey of Manufacturers (ASM) or Census of Manufacturers (CMF) in the year prior to bankruptcy, allowing us to measure TFP.[2] We then track the TFP at a given location in the five years after bankruptcy, using the same 2SLS strategy as in the main analysis.[3]

Tracking TFP is not possible in two situtations. First, TFP is not measured at locations that transition to manufacturing firms not included in the ASM/CMF sample or out of manufacturing altogether. In Table A.12 we assume this set of plants has the median TFP from the full ASM/CMF sample in a given year. However, assuming any other level of TFP or dropping these plants from the sample completely does not impact the size or significance of the results. Second, TFP is not defined for vacant locations. Because liquidation leads to higher instances of vacancy, the results are dependent on how the implied productivity of vacant locations is interpreted. Accordingly, in Table A.12 we present results where the TFP of vacant locations is set at various levels. In columns 1 and 2, we assume that vacant locations are unproductive by setting ln(TFP)=0 whenever a plant is vacant. Under this assumption, liquidation results in a sharp decline in TFP of 41.6% (based on the 2SLS estimates). Columns 3-6 show that even if vacant-plant TFP is set at the 10th or 20th percentile liquidation leads to a significant reduction in productivity.

[2]We use the ln(TFP) measure contained in the auxiliary Census ASM files, which is computed following the standard TFP estimation procedures outlined in Foster et al. (2001). Further, since the ASM and CMF do not cover the universe of manufacturing plants, we follow the previous literature and weight regressions by the inverse of the sampling weight. However, this weighting does not affect the results.

[3]Despite the much smaller sample size, the first stage remains strong with an F-stat of 13.

B Search Model

In this section we lay out a model of decentralized markets with two-sided search to study the effects of bankruptcy approaches, liquidation and reorganization, on asset allocation and utilization. The model builds on Gavazza (2011) and Mortensen and Wright (2002), who adapt the framework introduced by Diamond (1982). We start by briefly outlining the Gavazza (2011) model, and then introduce bankrupt sellers in the model.

B.1 Model Setup of Gavazza (2011)

Consider a model with continuous time and infinite horizon. There is a total mass $S' > 0$ of assets (which defines the thickness of the market), and a mass of $A = S' + B'$ firms in the economy, where S' are potential sellers, B' are potential buyers, and $B' > S'$ such that there is an excess demand for assets. Firms are risk neutral and discount the future at a positive rate $r > 0$. Firms are differentiated by an exogenous productivity shock, $z \geq 0$, which is drawn from a cumulative distribution function $F(z)$ that follows an independent stochastic process. Each firm receives a new draw from $F(z)$ at the instanteneous rate λ. Each firm can own either zero or one asset. A firm with productivity z chooses the endogenous utilization $h(z)$ of the asset to maximize the instantaneous payoff $\pi(z)$.[4]

Firms can either buy or sell assets by paying a search cost c to enter a decentralized asset market. Thus, the mass of active sellers S (active buyers B) is the subset of potential sellers S' (potential buyers B') that has paid the search cost c. Once a firm is an active buyer or seller, they make pairwise independent contacts with other interested firms at Poisson arrival times with intensity $\gamma > 0$, such that all traders are equally likely to be contacted and match randomly. We denote the probability that a buyer (seller) makes contact with a seller (buyer) as S (B), where S and B are the stocks of active sellers and active buyers. On aggregate, contacts between sellers and buyers occur continuously at a rate of γBS. Once an active buyer and an active seller meet, they negotiate a price to trade according to generalized Nash bargaining, where $\theta \in (0, 1)$ denotes the bargaining power of the buyer.

B.2 Solution Intuition

We discuss here the intuition behind the solution of the model, and refer readers to the appendix of Gavazza (2011) for the full solution concept. Each seller with productivity z can choose whether to put the asset up for sale. If so, the seller pays the search cost c and meets potential trading partners at rate γB. The seller also obtains flow of profit $\pi(z)$. Similarly, a potential buyer can pay the search cost c and meet active sellers at rate γS, or can wait and search later when his productivity changes. Thus, we have four categories of agents, namely active and non-active buyers and sellers. Let $V_B(z)$ be the value function of an active buyer, and $W_B(z)$ be the value function of a non-active buyer. Similarly, $V_S(z)$ and $W_S(z)$ are the value functions of active and non-active sellers, respectively.

Intuitively, a potential buyer prefers to be an active buyer when his productivity z is sufficiently high, and a potential seller prefers to be an active seller when her productivity is sufficiently low. When an active buyer and an active seller meet and trade, they become non-active sellers and buyers, respectively, at least until their productivity draw z changes. We present below the value functions of the active and inactive firms. These value functions pin down the equilibrium conditions and characterize the endogenous distribution of productivity and capacity utilization of active firms.

Central in the solution is how potential sellers' and buyers' cutoff values—the values at which potential sellers and buyers are indifferent between being active or inactive—change with the thickness of the market, that is with S', which in turn determines the (endogenous) number of contacts γBS. As highlighted by Gavazza (2011), the key economic force is that the trading technology exhibits increasing returns to scale. Hence, sellers' threshold value increases and buyers' threshold value decreases as the asset market gets thicker. As a result, in thicker markets, more assets reallocate to more productive firms, the average productivity of asset owners increases, and so does the utilization h of existing assets by firms.

[4] We select a specific functional form for $\pi(z)$ in the numerical illustration below, but leave it general for now.

B.2.1 Value Functions

The value functions characterize the objective function of active and inactive buyers and sellers. Consider a potential buyer, with productivity $z = b$ and no asset. The firm has two options: either pay the search cost c and look for sellers, or stay inactive. If the firm decides to be an *active buyer*, she pays the search cost c and her value function $V_B(b)$ satisfies:

$$\begin{aligned} &rV_B(b) = -c + \gamma S \int \max\{W_S(b) - p(b,s) - V_B(b), 0\} dG_S(s) + \\ &\lambda \int (\max\{V_B(z), W_B(z)\} - V_B(b)) dF(z) \end{aligned} \tag{1}$$

At any point in time, one of two things can happen. First, at rate γS, the buyer meets an active seller. If a trade occurs at price $p(b,s)$, he obtains a capital gain equal to $W_S(b) - p(b,s) - V_B(b)$ and becomes an inactive seller. This is the gain from becoming an inactive seller $W_S(b)$, minus the price paid $p(b,s)$ (which depends on productivity of seller s) and minus the value lost from no longer being an active buyer with productivity b. If a trade does not occur, he has no capital gain. Alternatively, the firm may receive a new productivity draw, at rate λ. After learning the new productivity, the buyer decides whether to remain an active buyer (with a capital gain equal to $V_{\mathrm{B}}(z) - V_B(b)$) or whether to become an inactive buyer (with a capital gain equal to $W_B(z) - V_B(b)$).

Similarly, the value function $V_S(s)$ of an *active seller* with productivity s satisfies the following value function:

$$\begin{aligned} &rV_S(s) = -c + \pi(s) + \gamma B \int \max\{W_B(s) + p(b,s) - V_S(s), 0\} dG_B(b) \\ &+\lambda \int (\max\{V_S(z), W_S(z)\} - V_S(s)) dF(z) \end{aligned} \tag{2}$$

An active seller receives an instantaneous payoff flow equal to the difference between her profitability $\pi(s)$ and the search cost c. At rate γB, she meets an active buyer. If trade occurs, she obtains a capital gain equal to $p(b,s) + W_B(s) - V_S(s)$ and becomes an inactive buyer. If trade does not occur, the firm has no capital gain. At rate λ, the firm receives a new productivity draw. After learning the new productivity, the firm decides whether to remain an active seller (with a capital gain equal to $V_S(z) - V_S(s)$) or whether to become an inactive seller (with a capital gain equal to $W_S(z) - V_S(s)$).

Turning to inactive firms, the value function of an *inactive buyer* does not depend on current productivity b since he does not operate an asset, and satisfies:

$$rW_B = \lambda \int (\max\{V_B(z), W_B\} - W_B) dF(z) \tag{3}$$

In contrast, the value function of the *inactive seller* does depend on current productivity s, and satisfies:

$$rW_S(s) = \pi(s) + \lambda \int (\max\{V_S(z), W_S(z)\} - W_S(s)) dF(z) \tag{4}$$

These equations imply that the flow value of an inactive trader is equal to the instantaneous profits (0 for a buyer, $\pi(s)$ for a seller) plus the expected capital gain as the productivity parameter evolves.

When an active buyer b and an active seller s meet and trade, the negotiated price is:

$$p(b,s) = \theta(V_S(s) - W_B) + (1-\theta)(W_S(b) - V_B(b)) \tag{5}$$

which is the solution to the following Nash bargaining problem:

$$\max_p [W_S(b) - p(b,s) - V_B(b)]^{\theta} [W_B + p(b,s) - V_S(s)]^{1-\theta}$$

Subject to: W_S(b)-$p(b,s) \geq V_B(b)$ and $p(b,s) + W_B \geq V_S(s)$

Next we show the equilibrium conditions that define the cutoff thresholds of buyers and sellers that determines their active participation in the market. These cutoff values also determine the endogenous stock of active buyers and sellers (S, B) in the market.

B.2.2 Characterizing the Equilibrium

Gavazza (2011) shows that there exists a reservation value R_B such that only buyers with productivity $b \geq R_B$ (and, hence, profits $\pi(b) \geq \pi(R_B)$) have positive gains from entering the asset market. Similarly, there exists a reservation value R_S such that only sellers with productivity $s \leq R_S$ (profits $\pi(s) \leq \pi(R_S)$) have positive gains from searching for buyers. Specifically, he finds that the distribution of active sellers and active buyers, as a function of their productivity shock, is as follows:

$$g_S(z) = \begin{cases} 0 & \text{for } R_S \leq z \\ \frac{f(z)}{F(R_S)} & \text{for } R_S > z \end{cases}$$

$$g_B(z) = \begin{cases} \frac{f(z)}{1-F(R_B)} & \text{for } R_B \leq z \\ 0 & \text{for } R_B > z \end{cases}$$

The threshold values (R_B, R_S), together with the endogenous stock of active buyers and sellers (S, B), are determined in a steady-state equilibrium such that active buyers are all potential buyers with productivity above R_B, and active sellers are all potential sellers with productivity below R_S. Next, we define the equilibrium conditions, as identified by Gavazza (2011).

Equilibrium Conditions

- The reservation values (R_B, R_S) satisfy the following indifference conditions:

$$c = \gamma S\theta \int \left(k_S \left(\pi(R_S) - \pi(s)\right) - \frac{\pi(R_S) - \pi(R_B)}{r + \lambda} \right) dG_S(s) \tag{6}$$

$$c = \gamma B(1-\theta) \int \left(\frac{\pi(b) - \pi(R_S)}{r + \lambda} - k_B \left(\pi(b) - \pi(R_B)\right) \right) dG_B(b) \tag{7}$$

where $G_S(s)$ and $G_B(b)$ are the cumulative distribution functions of active sellers and active buyers, respectively. $G_S(s)$ and $G_B(b)$ are derived from the probability density functions $g_S(s)$ and $g_B(b)$ defined above.

- Active buyers are all potential buyers with productivity above R_B, and active sellers are all potential sellers with productivity below R_S, i.e.:

$$B = B'(1 - F(R_B)) \frac{\lambda}{\lambda + \gamma S} \tag{8}$$

$$S = S' \frac{\lambda}{\lambda + \gamma B} F(R_S) \tag{9}$$

Below we illustrate how market thickness affects the equilibrium distribution of productivity, utilization, and stock of active buyers and sellers through a numerical solution based on Gavazza (2011). We then use this numerical illustration to discuss the consequences of different approaches to bankruptcy.

B.2.3 Numerical Illustration

To illustrate how market thickness affects equilibrium conditions, we fix values of the exogenous parameters and of $F(z)$, and then solve the model numerically.[5] More precisely, the numerical solutions illustrate how equilibrium conditions change with the increase of market thickness S', while holding the ratio of potential sellers (and thus, assets) S' and potential buyers B' constant.

[5] The numerical values of the exogenous parameters follow Gavazza (2011) and are: $\theta = 0.5$; $c = 15$; $r = 0.05$; $\gamma = 0.2$; $\lambda = 0.2$; $B' = 1.5S'$. $F(z)$ is the normal distribution with mean µ equal to 20 and standard deviation σ equal to 5.

We assume that the profit function $\pi(z)$ is positive for positive productivity shocks only.[6] Specifically, we assume that a firm that owns an asset chooses the endogenous utilization h of the asset to maximize the instantaneous payoff given by the difference between revenue $\alpha h\sqrt{z}$ and cost $h^2/2$ such that $\pi(z) = \alpha h\sqrt{z} - h^2/2$. Hence, the optimal capacity utilization is $h^* = \alpha\sqrt{z}$, and $\pi(z) = \frac{1}{2}\alpha^2 z$ are the instantaneous profits. Without loss of generality, we set $\alpha = \sqrt{2}$ so that a firm's instantaneous profitability is equal to its productivity, i.e.:

$$\pi(z) = \begin{cases} 0 & \text{if } z \leq 0 \\ z & \text{if } z > 0 \end{cases}$$

In Figure 6 below we replicate several features of the equilibrium of Gavazza (2011). In panel (a) we plot the behavior of the endogenous variables (R_S, R_B), which characterize the thresholds of buyer and seller firms to become active in the market. This plot is key to understanding the effects of market thickness on asset allocation. The plot shows that sellers' reservation value R_S increases and buyers' reservation value R_B decreases as the number of assets increases. When the asset market is thin, trading frictions are high and sellers choose to hold on to assets for longer periods of time in case their productivity z rises in the future. As market thickness increases, search frictions decline and the reservation values R_S and R_B converge.

Panel (b) shows that the asset holding time decreases as the mass of assets increases. This is because the sellers' cutoff value is higher, so the probability that assets are put on the market for sale is higher. Moreover, the meeting rate is higher due to the presence of more buyers and sellers, so assets trade faster. Panels (c) and (d) show that both average capacity utilization and asset owners' productivity increase with market thickness. This suggests that, on average, assets are more efficiently allocated when the market becomes thicker. We derive the precise expressions for average productivity, utilization and time to sale below, together with the expressions for the bankrupt sellers.

B.3 Introducing Bankrupt Sellers

We introduce two types of bankrupt sellers in the model: liquidated and reorganized sellers. We assume that bankrupt sellers are few in number and so do not affect equilibrium behavior of regular buyers and sellers.[7] The matching function in the economy, and thus the meeting probability with active buyers, depends on market thickness which determines equilibrium quantities of regular active buyers and sellers. The transaction price for liquidated and reorganized sellers, p_{liq} and p_{re} respectively, are set according to the same bilateral Nash bargaining discussed for the case of regular sellers. Since liquidated and reorganized sellers are facing different value functions, they also face different prices in the bilateral negotiations, as we discuss below.

B.3.1 Value Functions of Bankrupt Sellers

We start by defining the different value functions that bankrupt sellers are facing as passive or active sellers. Let $V_{liq}(z)$ be the value function of liquidated sellers who actively search, and $W_{liq}(z)$ be the value function of liquidated sellers who do not search. Similarly, let $V_{re}(z)$ and $W_{re}(z)$ be the value functions of active and inactive reorganized sellers, respectively.

Consider first the value function of liquidated sellers. Under liquidation, the firm ceases to exist, and liquidated sellers can no longer generate intermediate profit, so that $\pi_{liq}(z) = 0$, and they have zero productivity, i.e. $z = 0$. It follows that $V_{liq}(z)$ satisfies:

$$rV_{liq} = -c + \gamma B \int \max\{p_{liq}(b) - V_{liq}, 0\} dG_B(b) \tag{10}$$

[6]We make this assumption to allow for liquidated sellers. Specifically, as we discuss below, liquidation leads to firm shutdown, and thus we assume such sellers have productivity $z = 0$, which lead to a profit function that is equal to zero.

[7]This implies that the distributions of regular active buyers and sellers are determined in equilibrium, which dictates the characterics of the market with which bankrupt sellers interact.

An active liquidated seller has no intermediate profits and pays the search cost c. At rate γB, she meets an active buyer, and negotiate a price $p_{liq}(b)$ that depends on buyer's productivity only. If trade occurs, she obtains a capital gain equal to $p_{liq}(b) - V_{liq}$. Note that in contrast to regular sellers, the liquidated seller does not benefit from W_{liq}, since the firm ceases to exist and does not convert to a non-active buyer. If trade does not occur, the firm has no capital gain. In fact, liquidated seller will not always be willing to trade when meeting a buyer. A liquidated seller will trade with buyers only if the buyer's type is higher than the trading threshold B_{liq}, which is defined by:

$$p_{liq}(B_{liq}) = V_{liq} \tag{11}$$

That is, there may be cases in which a liquidated seller meets a low-productivity buyer, where $b < B_{liq}$, and will prefer to wait and meet a future buyer.[8] Moreover, because liquidated sellers shut down and do not generate intermediate profit, in nearly all cases they will choose to become active sellers. Only in extreme cases, in which the market is particularly thin, liquidated sellers may choose to become inactive, in which $W_{liq} = 0$. That will be the case if search cost c is higher than expected capital gains, as illustrated in equation 10. Hence, the decision of whether to become active seller depends on market characteristics only, and the distribution of active buyers in particular, and not on the dynamic evolution of seller productivity, as is the case for regular sellers.

In reorganization, the firm continues to operate and can still generate intermediate profits from the asset. However, due to agency problems, managers may continue to hold on to the assets inefficiently, despite the availability of productive potential buyers. We model agency costs as private benefits that managers receive from holding on to the asset. Specifically, we assume that the profit function of reorganized sellers is $\pi_{re}(z) = \pi(z) + \delta$, where δ captures the private benefits. Then, the value function for active reorganized sellers is:

$$\begin{aligned} rV_{re}(s) = {} & -c + \pi(s) + \delta + \gamma B \int \max\{p_{re}(b,s) + W_B - V_{re}(s), 0\} dG_B(b) \\ & + \lambda \int (\max\{V_{re}(z), W_{re}(z)\} - V_{re}(s)) dF(z) \end{aligned} \tag{12}$$

Hence, an active reorganized seller pays the search cost c, earns the instantaneous profit $\pi(s)$, and gains the private benefit δ for holding on to the asset. The private benefit makes the reorganized seller less willing to sell the asset. At rate γB, the reorganized seller meets an active buyer, and if trade occurs, she obtains a capital gain equal to $p_{re}(b,s) + W_B - V_{re}$.[9] Meanwhile, if trade does not occur, the reorganized seller has no capital gain. At rate λ, the firm receives a new productivity draw. After learning the new productivity, the firm decides whether to remain an active seller (with a capital gain equal to $V_{re}(z) - V_{re}(s)$) or to become an inactive seller (with a capital gain equal to $W_{re}(z) - V_{re}(s)$).

Reorganized sellers will trade with buyers only if the buyer's type is higher than the trading threshold B_{re}. From equation 12, this trading threshold is defined as the point where:

$$p_{re}(B_{re}, s) + W_B = V_{re}(s) \tag{13}$$

It is important to note that the agency cost δ increases the value of $V_{re}(s)$, which therefore raises this trading threshold and makes it less likely that a reorganized seller will sell the asset even after a buyer has been found.

Finally, non-active reorganized sellers have the following value function:

$$rW_{re}(s) = \pi(s) + \delta + \lambda \int (\max\{V_{re}(z), W_{re}(z)\} - W_{re}(s)) dF(z)$$

[8] In equilibrium, regular sellers always trade if a meeting occurs because of the adjustment of the search thresholds ensure that trade is profitable for both parties. This does not necessarily hold for liquidated sellers because once they sell the asset they do not convert to inactive buyers (as regular sellers do) and thus they do not receive W_B after selling the asset. Thus, in contrast to regular sellers, liquidated sellers may choose to wait for a more productive buyer. These cases are rare, however, since liquidated sellers do not generate intermediate profits while awaiting a new buyer.

[9] Note that we assume that once a reorganized seller sells her asset, she becomes a regular inactive buyer earning W_B. This assumption stems from the idea that financial distress and bankruptcy create the agency cost δ. Once the asset is sold, the buyer is no longer distressed and thus becomes a normal inactive buyer who will not earn δ if she buys another asset.

where the gains come only from the instanteneous profit and the private benefits. At rate λ, the firm receives a new productivity draw. After learning the new productivity, the firm decides whether to become an active seller (with a capital gain equal to $V_{re}(z) - W_{re}(s)$) or to remain an inactive seller (with a capital gain equal to $W_{re}(z) - W_{re}(s)$).

B.3.2 Search Thresholds

We calculate the search cutoffs for liquidated and reorganized sellers, that is, the productivity level R_{re} and R_{liq} that define whether they actively search in the market. That is, the search cutoffs satisfy $V_{re}(R_{re})$=$W_{re}(R_{re})$, and V_{liq}=W_{liq} respectively. To do so, we first calculate the equilibrium level of search thresholds R_S, R_B for regular sellers and buyers, and the mass of active agents S and B in the market. Then, given this distribution of potential buyers, we apply value iteration for the value functions of reorganized and liquidated sellers, to calculate the search thresholds R_{re} and R_{liq} for each level of market thickness, where market thickness is defined as S', the total amount of assets that could potentially be on the market.

Using the parameters from Section B.2.3, we illustrate how the bankrupt search thresholds are affected by market thickness in Panel (a) of Figure 6.[10] Liquidated sellers always choose to actively search for a buyer, since the active value function is always higher than the non-active value function, that is $V_{liq} > W_{liq}$, and therefore not reported in Figure 6 Panel (a). Meanwhile, due to the private benefits gained from holding the asset, reorganized sellers are less likely to become active sellers relative to regular sellers, as for every level of market thickness we have that $R_S > R_{re}$.

Apart from the search thresholds, it is also worth noting that both liquidated and reorganized sellers are facing trade thresholds, B_{liq} and $B_{re}(s)$, that need to be satisfied when meeting a buyer. The trade threshold B_{liq} is easily cleared for liquidated sellers because they do not receive intermediate profits from the asset and thus they nearly always sell when meeting a buyer. Meanwhile, the $B_{re}(s)$ trade threshold is more binding by the agency cost δ, as described above.

B.4 Holding Time

The different objectives faced by bankrupt sellers on asset allocation can have an impact on the holding time of the assets. Here we calculate the expected amount of time that regular sellers hold an asset, and compare it with liquidated and reorganized bankrupt sellers.

Holding Time for Regular Sellers

Consider first the case of regular sellers. We define the expected holding time as $T_V(s)$ for regular active sellers of type s, and T_W for regular inactive sellers. For the non-active sellers, the expected holding time is:

$$T_W = \frac{1}{\lambda} + \int_{-\infty}^{R_S} T_V(z) \cdot f(z)dz + \int_{R_S}^{\infty} T_W f(z)dz \tag{14}$$

There are three terms in the equation above. Since the seller is currently inactive, they will not become active unless they get a new productivity draw, and so the first term accounts for the expected time until the productivity level changes. The second term is the expected holding time when the new productivity draw is below the search threshold R_S and the seller becomes active. The third term represents the expected holding time when the new productivity draw is above R_S and the seller remains inactive. Similarly, the expected holding time for regular active sellers is:

$$T_V(s) = \frac{1}{\gamma B + \lambda} + \frac{\lambda}{\gamma B + \lambda} \left(\int_{-\infty}^{R_S} T_V(z) \cdot f(z)dz + \int_{R_S}^{\infty} T_W f(z)dz \right) \tag{15}$$

[10] In Figure 6 we set the agency costs parameter to $\delta = 0.5$. In Section VII in the paper we illustrate how the model predictions change with high agency costs, when setting the parameter to $\delta = 2.5$.

Here, the first term is the expected time until the seller either encounters a buyer in the market or changes productivity type. The second terms accounts for the possibility that the active seller will get a new productivity draw before finding a buyer and possibly become an inactive seller.[11]

Note that both terms T_W and T_V do not depend on firm productivity. After simplifying the terms T_W and T_V,[12] we can express the average holding time for regular sellers as a weighted average between that of an active and of an inactive seller, where the weights depend on the equilibrium distribution of sellers, namely:

$$\begin{aligned} T &= \int_{-\infty}^{R_S} T_V g_{S'}(z)dz + \int_{R_S}^{\infty} T_W g_{S'}(z)dz \\ &= T_V G_{S'}(R_S) + T_W(1 - G_{S'}(R_S)) \end{aligned} \tag{16}$$

Holding Time for Reorganized Sellers

Let the expected asset holding time for active reorganized sellers be $T_{re,V}(s)$, and the expected holding time for inactive ones be $T_{re,W}$. Then, following a reasoning analogous to that for regular sellers, we have that:

$$T_{re,W} = \frac{1}{\lambda} + \int_{-\infty}^{R_{re}} T_{re,V}(z) \cdot f(z)dz + \int_{R_{re}}^{\infty} T_{re,W} f(z)dz \tag{17}$$

and:

$$\begin{aligned} &T_{re,V}(s) = \tfrac{1}{\gamma B+\lambda} + \tfrac{\lambda}{\gamma B+\lambda}\left(\int_{-\infty}^{R_{re}} T_{re,V}(z) \cdot f(z)dz + \int_{R_{re}}^{\infty} T_{re,W} f(z)dz\right) \\ &+ \tfrac{\gamma B}{\gamma B+\lambda} P(p_{re}(\tilde{b}, s) + W_B < V_{re}(s)) T_{re,V}(s) \end{aligned} \tag{18}$$

Unlike the case of regular sellers, there is an extra (third) term in the equation for $T_{re,V}$ to capture the fact that even when the reorganized sellers meet a buyer, a sale is not guaranteed. This is because the agency cost δ can prevent a reorganized seller from being willing to trade, whereas all normal sellers are willing to trade with normal buyers in equilibrium. Therefore, the expected time might be longer when $p_{re} + W_B < V_{re}(s)$, in which case the reorganized seller would prefer to wait for another buyer with higher productivity and thus higher willingness to pay.

After re-arranging the terms and iterating, we obtain a final expression the expected holding time for reorganized sellers:[13]

$$T_{re} = \int_{-\infty}^{R_{re}} T_{re,V}(z) \cdot g_{S'}(z)dz + \int_{R_{re}}^{\infty} T_{re,W} \cdot g_{S'}(z)dz$$

[11] A third term exists here with probability $\frac{\gamma B}{\gamma B+\lambda}$ in which the seller meets a buyer. But since a meeting always leads to a transaction for regular sellers, this adds no additional holding time.

[12] The two terms can be re-written as:

$$\begin{cases} T_V = \frac{1}{\gamma B+\lambda} + \frac{\lambda}{\gamma B+\lambda}\left(T_V F(R_S) + T_W(1 - F(R_S))\right) \\ T_W = \frac{1}{\lambda} + T_V F(R_S) + T_W(1 - F(R_S)) \end{cases}$$

[13] In the derivations, we first define:

$$T_0 = \int_{-\infty}^{R_{re}} T_{re,V}(z) \cdot f(z)dz + \int_{R_{re}}^{\infty} T_{re,W} f(z)dz$$

Then we express the expected time to sale for active and inactive reorganized sellers, respectively, as:

$$T_{re,V}(s) = \frac{1 + \lambda T_0}{\lambda + \gamma B \cdot P(p_{re}(\tilde{b}, s) + W_B \geq V_{re}(s))}$$

$$T_{re,W} = \frac{1}{\lambda} + T_0$$

Holding Time for Liquidated Sellers

Except in the most extreme cases of market thickness, which we will ignore, all liquidated sellers actively search for a buyer in the economy. The expected holding time, T_{liq}, equals:

$$T_{liq} = \frac{1}{\gamma B} + P(p_{liq}(\tilde{b}) < V_{liq}) \cdot T_{liq} \tag{19}$$

where the first term captures the expected holding time if the seller does not find a buyer. This term shows that liquidated sellers time to sell heavily depends on the distribution of active buyers, and thus, market thickness. The second term captures cases in which the liquidated seller, despite having found a buyer, prefers to wait since $p_{liq}(\tilde{b}) < V_{liq}$. Re-arranging the terms, we can re-write the expected holding time for a liquidated seller as:

$$T_{liq} = \frac{1}{\gamma B \cdot P(p_{liq}(\tilde{b}) \geq V_{liq}))} \tag{20}$$

Numerical Illustration of Holding Time

In Panel (b) of Figure 6 we investigate the impact of market thickness on expected holding time for all types of sellers. Liquidated sellers have a much shorter holding times, when compared to regular sellers. This is due to the impatience to sell that arises from their inability to produce intermediate profits from the asset. In contrast, reorganized sellers have a longer holding time when compared to regular sellers, due to the private benefits from holding on to the assets. Moreover, as the market thickness increases, the expected holding time declines for all sellers, as the likelihood of finding a buyer increases. Finally, the gap in expected holding time between liquidated and reorganized sellers declines with market thickness, since reorganized sellers become more willing to sell as the probability of finding a buyer increases.

B.5 Asset Utilization

In this section we calculate the expected lifetime utilization of an asset, and explore how this utilization varies with the type of seller that initially owns the asset.

Asset Utilization for Regular Sellers

We start by calculating the expected lifetime utilization of assets initially held by regular sellers. The utilization of an asset depends on current level of utilization, holding time of the asset, and the type of future buyers. Denote with $U_V(s)$ the expected utilization of an asset currently held by active sellers of type s, and by $U_W(s)$ the expected utilization of an asset currently held by inactive seller of type s. Thus, $U_V(s)$ applies only when $s \leq R_S$, and $U_W(s)$ applies only when $s > R_S$. Let $T_1 \sim \exp(\lambda)$, $T_2 \sim \exp(\gamma B)$. T_1 denotes the time to the next change in firm productivity, and T_2 denotes the time to meet a buyer for an active seller. The expected utilization is:

$$\begin{aligned} U_V(s) = E[\int_0^{min(T_1,T_2)} h(s)e^{-rt}dt] + E[e^{-r(min(T_1,T_2))}\mathbf{1}(T_1 \leq T_2)\left(\int_{-\infty}^{R_S} U_V(z)dF(z) + \int_{R_S}^{\infty} U_W(z)dF(z)\right)] \\ + E[e^{-r(min(T_1,T_2))}\mathbf{1}(T_1 > T_2)U_W(\tilde{b})] \end{aligned} \tag{21}$$

The first term represents the expected utilization for the current level of productivity s until either productivity changes or a trade occurs. The second term captures the expected utilization after a productivity shift (combining both the expected utilization as an active seller and as an inactive seller). The third term refers to the case in which the seller meets a buyer and a trade occurs and the new buyer becomes an inactive seller. We can simplify the above equation and re-write it as:

$$U_V(s) = \frac{h(s)}{\lambda + \gamma B + r} + \frac{\lambda}{\lambda + \gamma B + r}\left(\int_{-\infty}^{R_S} U_V(z)dF(z) + \int_{R_S}^{\infty} U_W(z)dF(z)\right) + \frac{\gamma B}{\lambda + \gamma B + r}E[U_W(\tilde{b})] \tag{22}$$

On the other hand, the expected utilization for an inactive seller is simply the sum of current asset utilization and the expected utilization once a new productivity shock hits, i.e.:

$$U_W(s) = \frac{h(s)}{r+\lambda} + \frac{\lambda}{r+\lambda}\left(\int_{-\infty}^{R_S} U_V(z)dF(z) + \int_{R_S}^{\infty} U_W(z)dF(z)\right) \tag{23}$$

As a result, we can express the average utilization for regular sellers as the expected utilization of active and inactive sellers, taking into account their distribution in equilibrium:

$$\bar{U} = \int_{-\infty}^{R_S} U_V(s)g_{S'}(s)ds + \int_{R_W}^{\infty} U_W(s)g_{S'}(s)ds \tag{24}$$

Asset Utilization for Reorganized Sellers

Denote the expected lifetime utilization of an asset under active reorganized sellers by $U_{V,re}(s)$, and the one of inactive reorganized sellers by $U_{W,re}(s)$. Let $T_{re,1} \sim \exp(\lambda)$, $T_{re,2} \sim \exp(\gamma B)$ be defined analogously to the case of regular sellers above. It follows that the expected utilization of active reorganized sellers is:

$$\begin{aligned} U_{V,re}(s) = E[\int_0^{min(T_{re,1},T_{re,2})} h(s)e^{-rt}dt] \\ +E[e^{-r(min(T_{re,1},T_{re,2}))}\mathbf{1}(T_{re,1} < T_{re,2})(\int_{-\infty}^{R_{re}} U_{V,re}(z)dF(z) + \int_{R_{re}}^{\infty} U_{W,re}(z)dF(z))] \\ +E[e^{-r(min(T_{re,1},T_{re,2}))}\mathbf{1}(T_{re,1} \geq T_{re,2})\left(U_W(\tilde{b})\mathbf{1}(p_{re}(\tilde{b},s)+W_B \geq V_{re}(s)) + U_{V,re}(s)\mathbf{1}(p_{re}(\tilde{b},s)+W_B < V_{re}(s))\right)] \end{aligned} \tag{25}$$

Note that the third term includes two scenarios. The first scenario, the reorganized seller and buyer reach an agreement, and therefore the expected utilization of the buyer is incorporated. In the second scenario, the reorganized seller is not willing to sell the asset, and therefore remains with the asset. This equation can be simplified and re-written as:

$$\begin{aligned} U_{V,re}(s) = \frac{h(s)}{\lambda+\gamma B+r} + \\ \frac{\lambda}{\lambda+\gamma B+r}\left(\int_{-\infty}^{R_{re}} U_{V,re}(z)dF(z) + \int_{R_{re}}^{\infty} U_{W,re}(z)dF(z)\right) + \\ \frac{\gamma B}{\lambda+\gamma B+r}\int_{R_B}^{\infty}(U_W(b)\mathbf{1}(p_{re}(b,s)+W_B \geq V_{re}(s)) + U_{V,re}(s)\mathbf{1}(p_{re}(b,s)+W_B < V_{re}(s)))dG_B(b) \end{aligned}$$

This utilization level therefore is analogous to that of regular sellers, except that it includes cases in which active reorganized sellers meet a buyer but are unwilling to trade due to the agency cost δ. Similarly, the expected utilization of the non-active reorganized sellers is a combination of the current level of utilization and the expected utilization after a change in productivity level:

$$U_{W,re}(s) = \frac{h(s)}{\lambda+r} + \frac{\lambda}{\lambda+r}\left(\int_{-\infty}^{R_{re}} U_{V,re}(z)dF(z) + \int_{R_{re}}^{\infty} U_{W,re}(z)dF(z)\right)$$

Therefore, the average utilization for reorganized sellers is given by:

$$\bar{U}_{re} = \int_{-\infty}^{R_{re}} U_{V,re}(s)g_{S'}(s)ds + \int_{R_{re}}^{\infty} U_{W,re}(s)g_{S'}(s)ds \tag{26}$$

Asset Utilization for Liquidated Sellers

Liquidated sellers are active sellers and they cannot utilize the asset while searching for a buyer. Denote the time to meet a buyer by T, where $T \sim \exp(\gamma B)$. Then, the expected asset utilization of a liquidated seller is:

$$U_{liq} = E[e^{-rT}\left(U_W(\tilde{b})\mathbf{1}(p_{liq}(\tilde{b}) \geq V_{liq}) + U_{liq}\mathbf{1}(p_{liq}(\tilde{b}) < V_{liq})\right)$$
$$= \frac{\gamma B}{r + \gamma B}\int_{R_B}^{\infty}(\mathbf{1}(p_{liq}(b) \geq V_{liq})U_W(b) + U_{liq}\mathbf{1}(p_{liq}(b) < V_{liq}))dG_B(b) \tag{27}$$

Numerical Illustration of Asset Utilization

We plot the average asset utilization across different seller types in Panel (c) of Figure 6. In thin markets, liquidation leads to lower utilization compared to reorganization. However, as the markets become thicker, utilization in liquidation grows faster than in reorganization because liquidated sellers are more exposed to market conditions. Subsequently, there is a crossing point where asset utilization in liquidation becomes greater than in reorganization. Intuitively, liquidated sellers can quickly reallocate the asset to more productive buyers when markets are thick because they have no incentive to hold on to the asset. In contrast, reorganized sellers are slower to sell because of the private benefits from holding on to the asset and the asset's ability to generate intermediate profits.

B.6 Average Productivity

We define the average productivity of an asset as the lifetime average productivity of its owner (and potential seller). As discussed in Gavazza (2011), for any production function with complementarity between productivity z and capacity utilization h, the optimal capacity utilization is an increasing function of productivity. The derivations for average productivity therefore are similiar to utilization, and one can simply replace h^* with productivity z.

We illustrate the relationship between average owners' productivity across different seller types and how it changes with market thickness in Panel (d) of Figure 6. In thin markets, the average productivity is higher in reorganization because it is difficult for sellers of liquidated assets to find a productive buyer. However, as markets become thicker, the average productivity of assets in liquidation increases sharply and the gap between productivity in reorganization and liquidation shrinks and reaches a point where productivity is higher in liquidation.

B.7 The Competitive Walrasian Equilibrium

In this section we explore an important benchmark of allocative efficiency captured by the Walrasian equilibrium. We follow the approach of Mortensen and Wright (2002) and Rubinstein and Wolinsky (1985) to characterize the Walrasian equilibrium as the analog of the competitive outcome, where search frictions and agency costs go to zero. That is, we calculate the equilibrium values of search thresholds, utilization, and productivity letting c, γ, and δ go to zero.

In the Walrasian equilibrium, we denote by R^* the threshold at which the asset holders are firms in the economy with productivity type $z \geq R^*$. That is, when $z < R^*$ asset holders sell their asset and no longer hold it. Following Mortensen and Wright (2002), when search frictions go to zero, R^* must satisfy:

$$1 - F(R^*) = \frac{S'}{S' + B'} \tag{28}$$

and the distribution of these asset holders is:

$$g^*_{S'}(z) = \frac{f(z)}{1 - F(R^*)}\mathbf{1}(z \geq R^*) \tag{29}$$

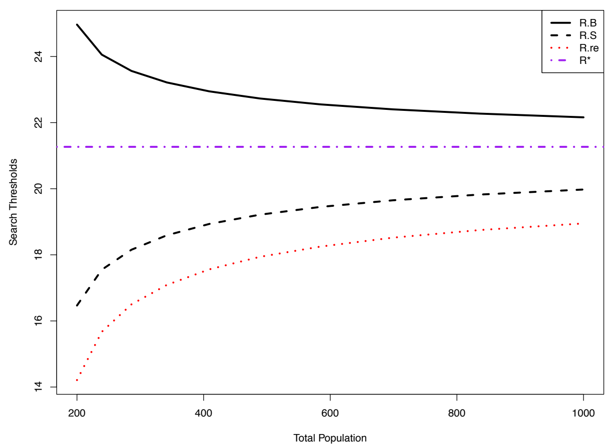
The threshold R^* is illustrated by the purple dot-dashed line in Panel (a) of Figure 6. As the figure shows, and as highlighted by Gavazza (2011), as market thickness increases frictions vanish, and the search thresholds R_S and R_B converge to their common limit which is given by the Walrasian benchmark R^*.

In Panels (c) and (d) of Figure 6, we also plot the Walrasian equilibrium values of utilization and productivity. When search frictions go to zero, the type s seller's asset utilization is $U^*(s) = \frac{h(s)}{r}$, and the average market utilization is $\overline{U^*} = \int_{-\infty}^{\infty} \frac{h(s)}{r} g^*_{S'}(s)ds$. Similarly, type s sellers' productivity is $H^*(s) = \frac{s}{r}$, and the average productivity in the market is $\overline{H^*} = \int_{-\infty}^{\infty} \frac{s}{r} g^*_{S'}(s)ds$.

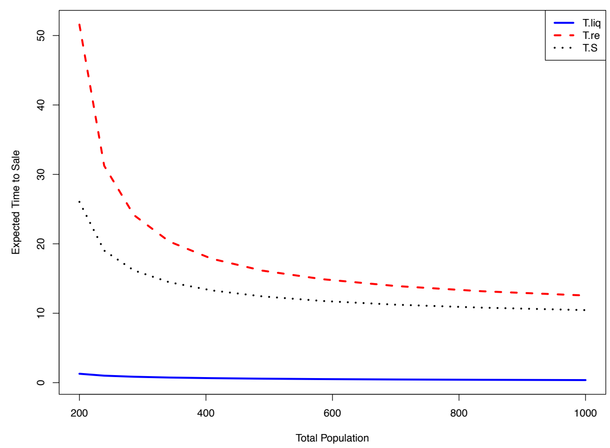
The plot shows that the average utilization and productivity converge to the Walrasian benchmark as market thickness increases. It is interesting to note that both the utilization and productivity levels in the Walrasian equilibrium are significantly above the utilization in reorganization and liquidation (and regular sellers). Intuitively, higher average utilization and productivity suggests that we draw closer to allocative efficiency when frictions do not exist. Therefore, one can interpret the results as suggesting that in thin markets the allocation of reorganized assets is closer to the competitive equilibrium and allocative efficiency because they have higher utilization and productivity than liquidated assets.

Figure 6
Model with Bankrupt Sellers

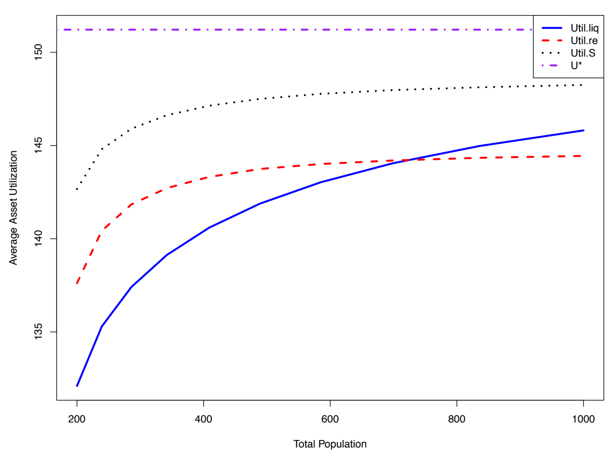
This numerical illustration captures the key insights from the basic model with respect to search thresholds, time to sale, asset utilization, and average productivity of asset users. In all figures, black solid lines represent regular buyers, black dashed lines are for regular sellers, red dashed lines represent reorganized sellers, and blue solid lines represent liquidated sellers. Because liquidated sellers always choose to enter the asset market, their search threshold is not displayed in Panel (a). In panels (a), (c), and (d) the purple dot-dashed line represents the Walrasian equilibrium in which search costs and agency costs go to zero.



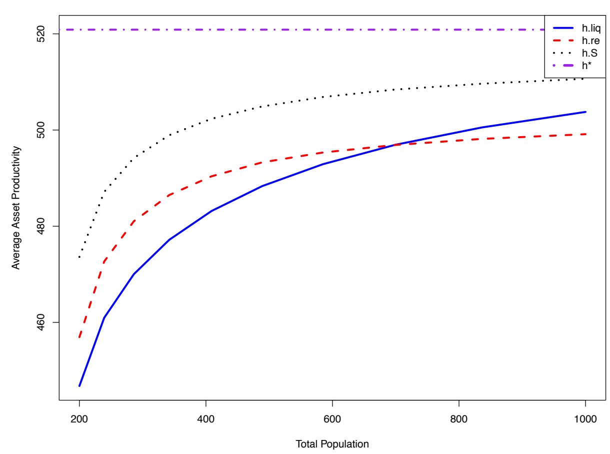
(a) Search Thresholds



(b) Time to Sale



(c) Asset Utilization



(d) Asset Productivity

C Matching Bankruptcy Filings to Census Data and Sample Selection

A first step in our analysis is to match bankruptcy filings data from LexisNexis to the Longitudinal Business Database (LBD) maintained by the Census Bureau. In this appendix we describe this matching process.

The data from LexisNexis contains individual Chapter 11 bankruptcy filings obtained directly from the U.S. Court system. When a firm files for bankruptcy, each individual legal entity that is seeking bankruptcy protection must create its own individual bankruptcy filing. Thus, it is common for firms to have multiple associated filings, which are all assigned to the same bankruptcy judge and are typically jointly administered. Importantly, the LexisNexis data contains information on both the bankruptcy judge and whether the case remained in Chapter 11, was converted to Chapter 7, or was dismissed from court entirely. For the purposes of our analysis, we focus only on firms that were treated with either Chapter 7 or Chapter 11. In total, our sample contains 67,810 unique bankruptcy filings.

We use the employer identification number (EIN), contained in both the bankruptcy filing and the LBD, to match the two datasets. Firm can have multiple EINs if they have separate subsidiaries for tax purposes. Further, multiple establishments in the BR can pertain to the same EIN. Thus, an EIN is an identifier somewhere between the level of the firm and the establishment. We use the set of all EINs associated with bankruptcy filings in the LexisNexis data and identify all plants in the LBD with the same EIN that were active in the year of the bankruptcy filing. This is the initial set of plants in our sample. In total, we match about 45,000 bankruptcy filings to over 141,000 unique establishments in the LBD, with a match rate of 65%.

Since the LBD covers the entire non-farm private sector of the U.S., it may seem odd that our match rate is not higher. One reason for this is that only businesses that have at least one employee are included in the LBD, while every unique legal enitty of a firm (each with a separate EIN) must create a separate bankruptcy filing. Thus, in the list of bankruptcy cases, we appear to have a substantial number of EINs that have no associated employees and are thus not in the LBD. Since these EINs are less likely to have commercial real estate assets, omitting them from our sample should not bias our estimates. Our match rate of 65% is similar to that in other studies that have used the LBD, such as Davis et al. (2014). Further, to ensure that the matching process is as comprehensive as possible, we also attempt to use the business names in the bankruptcy filings to match to the BR. However, this approach did not improve the match rate relative to the EIN matching, and therefore we focus exclusively on the latter.

From the initial set of 141,000 matched plants, we remove plants that only have P.O. box addresses or have missing addresses altogether, since we need a complete address to link establishments over time. Further, since occasionally firms may use accounting firms to report their information, we remove all accounting firms and any plant whose address matches that of an accounting firm from the sample. These restrictions leave us with a final sample of 129,000 plants, belonging to 28,000 unique firms.[14]

[14]In a small number of cases, firms with multiple EINs only partially matched to the LexisNexis data. This can happen if, for example, one subsidiary of a firm files for bankruptcy while other subsidiaries do not. In these cases, we only include establishments belonging to the bankrupt EIN in our sample, since it is unclear how the other establishments belonging to the firm are affected by the bankruptcy.

D Address Matching Algorithm

A principal goal in this paper is to track the economic activity at specific locations over time and across occupancy changes. The LBD links establishments over time only when the user of a location keeps the same name. Thus, only in cases where the establishment maintains the same name asset sales are tracked in the LBD. In the majority of cases, however, the new occupant has a different name and thus the transaction will be recorded as a "death" and a "birth," so that the economic activity at the location is not linked between the old and the new plant. In this appendix, we describe in detail the algorithm used to link geographic locations over time using the LBD.

D.1 Address Cleaning and Sample Selection

Prior to matching any addresses, we first define the sample of plants we are interesting in linking and clean their addresses. We begin with an initial set of 129,000 bankrupt establishments that matched to the set of Chapter 11 bankruptcy filings. From this group, we set aside those that survive (or are sold but continue to be linked in the LBD) for at least five years after their bankruptcy filing, as there is no need to track these plants. This leaves us with 89,000 total establishments that are shut down at some point, which we attempt to match to future establishment births located in the same addresses. For ease in exposition, we will refer to this dataset as the "DBP," for "dead bankrupt plants."

We next collect addresses from the Business Register (BR) for the entire LBD from 1992 - 2010. The BR contains both a physical address and a mailing address for each plant. The matching algorithm uses the physical address whenever possible, as this reflects the actual geographic location of the plant, but also attempts to match using the mailing address in cases where the physical address is not provided, on the assumption that in such cases the mailing address is likely the same as the physical address.

For each LBD plant we also bring in addresses reported in the Economic Censuses, which occur in 1992, 1997, 2002, and 2007 during our sample period. During these years, the Census Bureau itself collects detailed information on each establishment, rather than relying on tax data.[15] Thus, we would expect addresses reported in these years to be the most accurate. For each plant in the LBD in a given year, we merge addresses from the census before and after, and attempt to merge using those addresses as well. Hence, for a given plant there can be up to six different addresses:

1. Physical address
2. Mailing address
3. Physical address from prior census
4. Mailing address from prior census
5. Physical address from next census
6. Mailing address from next census

However, it is extremely rare for a plant to actually have six different addresses associated with it. In the vast majority of cases the physical and mailing addresses are the same, as are those from census years. Further, many plants do not survive across two censuses, and hence they will not have addresses from both the prior and next censuses.

Before matching, we use a combination of address cleaning algorithms from the NBER Patent Project, Wasi and Flaaen (2014), and our own code to prepare the addresses for matching. In this process, we carefully abbreviate all common words and separate street numbers and unit numbers from the name of the street using the United States Postal Service (USPS) formal algorithm. For example, an address of "123 South Main Street Suite 444" would be separated into three pieces: the street number "123," the street name "S MAIN ST," and the unit number "444." We also clean city names and abbreviate all states to standard USPS abbreviations, although this matters little as the zip code is a better identifier for matching because it is nested within cities (usually) and states (always).

[15] In non-census years, the LBD is based on information obtained from IRS tax records, rather than information collected directly by the Census Bureau.

D.2 Identifying Non-Unique Locations

Another important issue in linking geographic locations is dealing with non-unique addresses, which occur when multiple businesses are located in the same building, such as in office buildings or shopping centers. While in some of these cases we could in principle identify individual establishments by their unit number, in practice the reporting of unit or suite numbers is not always consistent over time, especially across ownership changes. Further, office numbers can be easily changed and offices can be combined or split as locations are repurposed to new uses.

For these reasons, we ignore unit/office/suite numbers in our matching process completely. Instead, we first identify non-unique plant locations, and take this information into account when allocating employment and wages to reallocated plants, as described below in Section D.5. More importantly, as shown in Appendix Table A.8, the results hold for various subsamples of the data that exclude addresses that have mutiple establishments within the same location. In this section we describe the process for identifying these non-unique locations.

First, for each plant in DBP, we identify a single address that we will use to track economic activity at that location. We do this according to the following hierarchy:[16]

1. Use the physical address in the year of death (available for approx. 90% of plants)
2. Use the physical address from the census prior to death if physical address at death is not available (used for approx. 2% of plants)
3. Use the mailing address in the year of death if no physical address is available (used for approx. 7% of plants)
4. Use the mailing address from the census prior to death if no other address is available (used for approx. 1% of plants)

This selected address is the key unique address at which we wish to follow economic activity for five years after the bankruptcy filing, and must therefore check if the address is unique for the bankrupt firm. We match each of these addresses to the LBD in year *t-1*, the year before the plant shutdown. To link the addresses in this and future matches, we use the Stata module *reclink2*, developed by Wasi and Flaaen (2014). *reclink2* allows for fuzzy matching, and further allows us to place different weights on the importance of different components of the address. In our matching, we require both the zip code and the street number to match exactly, but allow the street name and city name to differ slightly. As stated previously, we do not match on unit and suite numbers at all in this process, as the goal is to identify all plants associated with a given address in the year before death.

While this matching process allows for street names to differ slightly (e.g. "S MAIN ST" will match to "S MIAN ST"), we take care to remove matches where streets are numbered and the street numbers do not match exactly. For example, we do not wish to match a plant located at 123 14th ST to one located at 123 15th ST, even though these addresses differ by only a single character.

We match the DBP addresses to both physical addresses in the LBD first, and then to mailing addresses of LBD plants that do not have a physical address. As before, the vast majority of plants have a physical address, and we only use the mailing address where necessary. This matching process identifies all establishments associated with a specific address in the LBD in the year prior to the bankrupt establishment's death.

With this set of matches in hand, we count the total number of active plants at each DBP address in the year prior to death. Addresses with only a single match (the dead bankrupt plant itself), are unique locations where there was a single active establishment prior to bankruptcy. Meanwhile, addresses that have multiple establishments are deemed "non-unique," and care must be taken to allocate future employment at these locations.

To aid in calculating employment and payroll allocated to a bankrupt plant after a plant's death, we also calculate the "number of vacancies" at each address in each year after the bankruptcy filing. This is defined as the number of establishments that have died in that location between the bankruptcy filing and

[16]Note that, because plants in the DBP shut down, none of them have addresses available in the next census.

given year, and annotated $v_{p,t}$, where p indexes plants and t indexes years. For unique locations, the number of vacancies will be zero before the bankrupt plant's death, and 1 after it dies. However, for non-unique locations the number of vacancies depends on the death dates of non-bankrupt plants as well. For example, suppose there are 5 plants active in a location in 1998, one of which goes bankrupt and dies in 1999. If the other 4 plants are still alive in 1999, then $v_{p,1999}$=1. If 2 more plants die in 2000, then $v_{p,2000}$=3. If the other 2 plants survive past 2003 (5 years after the bankruptcy filing), then $v_{p,2000} = v_{p,2001} = v_{p,2002} = v_{p,2003} = 3$. We use this number of vacancies to divide employment at newly born plants at the address of plant p across the number of vacant units at the location, as described in Section D.5 below.

D.3 Address Matching After Bankruptcy

We next take the plants in DBP and match them to LBD plants that are born subsequent to their death. We do this by looping over all years from 1992 to 2010 and searching the LBD in each year for plants that are born that match addresses of dead plants in the DBP. Specifically, in year t of the loop the algorithm follows the following process:

1. Identify all plants in the DBP that died in or prior to year t, but whose bankruptcy filing date was after year $t-5$ (since we only follow plants for 5 years after their bankruptcy filing). This is the set of plants we will attempt to match in this year of the loop.

2. Identify all potentially matching plants in the LBD. These are plants that were active in year t and that have an address that matches a house number-zip code combination of the DBP. In addition, plants must have valid birth years. Specifically, the birth year must be:

   (a) After the census before the minimum filing year of the set of DBP plants identified in step 1 AND

   (b) Before the census after the maximum filing year of the set of DBP identified in step 1.[17]

3. Match the DBP plants from step 1 with the LBD plants identified in step 2 using *reclink2*, as described above.

4. Filter out bad matches by eliminating matches where:

   (a) A DBP plant matched to itself

   (b) The LBD plant was born before the death of the DBP plant, and hence could not have replaced the DBP plant.

   (c) The address match was incorrect due to numbered streets matching, as described above.

5. Repeat steps 3 and 4 for each of the following addresses in the LBD:[18]

   (a) Physical address

   (b) Mailing address

   (c) Physical address from prior census

   (d) Mailing address from prior census

   (e) Physical address from next census

   (f) Mailing address from next census

6. Save the full set of matches.

[17]We focus on births between census years rather than filing years to account for inexact birth and death years, as described later in this appendix.

[18]Recall that for each DBP we only use a single address.

We repeat this process for each year in our sample period, leaving us with a set of all new births at the same addresses of dead bankrupt plants. In section D.5 below we describe how we aggregate cases with multiple new births. First, we note two important aspects of the matching algorithm.

Between censuses, the LBD obtains information on plant births and deaths (and employment and payrolls) through IRS tax records as well as surveys conducted by the U.S. Census Bureau. Importantly, the Census Bureau surveys cover all firms with more than 250 employees, and so information on plant births and deaths belonging to these firms is accurate in all years. Further, exact birth and death years of plants belonging to single-establishment firms are known simply by when the firm enters or exits the IRS tax data. However, birth and death years for plants belonging to multi-establishment firms with less than 250 employees cannot be known exactly, since taxes are reported at the firm level and information on plants is only obtained every 5 years via census. The birth and/or death years for these plants is not known exactly, although it is known that it occurred between two given census years. For example, a small firm may have 2 establishments in the 1997 census and then grow to 3 plants in 2002. We then know then the 3rd plant was born between 1997 and 2002, but we do not know the exact year. A similar situation can arise with death years. When this occurs, we allow plants to match as long as it is possible that the birth could have been after the death of the bankrupt plant. This affects less than 2% of our matches and does not appear to bias our estimates in any way.

The second aspect of the linkage algorithm that is important to point out is that once a bankrupt plant has matched to a newly opened establishment we do not remove the bankrupt plant from the set of addresses we wish to match. For example, suppose that Plant A, located at 123 Main St., goes bankrupt and dies in year t, and that we subsequently find that Plant B was born at 123 Main St. in year $t+2$. Even though we have already found a match, we continue to search for plants that open at 123 Main St. in years $t+3$, $t+4$, and $t+5$. We continue to match in this fashion to account for the fact that there can be multiple establishments at the same address, even if the original plant was uniquely located. That is, even if Plant A was the only establishment located at 123 Main St. in year t, it is possible for Plant B and Plant C to share that space later on, in which case we should allocate both the employment of Plant B and that of Plant C to 123 Main St. Further, if Plant A was not uniquely located (e.g. if 123 Main St. was shopping mall), we cannot be sure that Plant B filled Plant A's spot, and therefore we wish to find all possible matches for this location even after Plant B has been identified as a possible match.

D.4 Verifying match quality

Because a high percentage of the plants in our sample close after filing for bankruptcy, it is vital that the linking algorithm be accurate in finding new economic activity occurring at each address. In particular, if the algorithm is too strict, we will miss some matches that should be made, thereby biasing downwards the estimates of economic activity at closed plants – which disproportionately come from cases that were converted to Chapter 7.

To address these concerns, we took the full sample of plants that closed but did not match to a new plant within 5 years of the bankruptcy filing (34,000 plants), and matched them to the LBD 5 years after their bankruptcy filing again, but this time merging on only zip code and street number (not street name, city, or state). This allows for complete flexibility in street names, which are the item that tends to vary the most across addresses. In this matching process, we find that 86% of these plants do not match to any plant in the LBD. That is, there was no plant in the entire LBD that was born after the original establishment closed that had the same zip code and street number for 86% of the cases. Further, we then took a random subsample of 500 of the cases which did have a match on street number and zip code (out of about 5,000 total, so this is a 10% subsample), and manually checked if the street names were similar but did not match using the fuzzy matching algorithm outlined above. We find that only 22% (112 of the 500) were potentially on the same street.[19] Assuming our subsample is representative, this would mean that only 22% of the 14% of firms that did have a match were actually good matches that were missed by our algorithm. Multiplying these percentages together (22%*14%=3%), we estimate that 97% of the plants that were not matched have

[19]We tried to be as generous as possible in determining whether two plants are a good match. For example, a match of a street name of "Herald Court Mall" to "Herald" or "Mall" would be counted as a match, even though there are potentially other streets in the same zip code with the word "Herald" or "Mall."

no possible match in the LBD. We thus feel confident that we are not missing many matches that should be made.

The flip side of this problem is also important: we must be sure that we are not incorrectly matching plants that were not at the same address. The reclink2 algorithm generates a match score, scaled from 0-1, that measures how closely the addresses match. By default, reclink2 uses a threshold of 0.6 as the minimum score for a match, but we opt for a stricter 0.9. In our data, 95% of all matches have a score higher than 0.987, with 58% being perfectly matched. The 1st percentile of our match scores is 0.909. Even among this set with lower match scores, we manually verify that the vast majority are correctly paired.

A final potential problem is that zip codes may be altered over time, thereby preventing us from making a match because we require zip codes to match exactly. The United States Postal Service lists zip code changes in their Postal Bulletins, available online at www.about.usps.com. From 2013-2015, on average only 8 zip codes were altered per year, out of a total of over 43,000 zip codes. Based on this, it does not appear that zip code changes will affect a large number of our addresses.

An related concern is that unmatched real estate assets, which we classify as vacant because they do not appear in the LBD, are in fact converted to a different use, such as residential homes or parks. We explore whether this is the case using data from CoreLogic, a data vendor that compiles the universe of all real estate transactions in the US. Reassuringly, we find that commercial real estate assets are converted into non-commercial types of real estate (residential, parks, etc.) in less than 1.5% of all transactions. This is not surprising, in light of the rigidity imposed by zoning regulations that restrict the nature of usage of real estate assets in commercial areas (Gyourko et al. (2008)).

D.5 Consolidating matches

At the end of the matching process described above, we potentially have multiple matches for each dead bankrupt plant. This is by design, as it allows us to account for the fact that multiple establishments may be located at the same address. The end goal of this process is to estimate the economic activity (in terms of total employment and total payroll) occurring at a location over time. This section describes how we consolidate employment and payroll at all matched plants to get this measure.

A key component of this calculation is the number of vacant units at a given address in year t, denoted $v_{p,t}$ and described in Section D.2 above. Using this variable, we calculate total employment for a location pertaining to a bankrupt plant p in year t as

$$TotalEmp_{p,t} = \sum_j \frac{emp_{j,p,t}}{v_{p,k}}$$

where j indexes newly born plants that matched to dead bankrupt plant p in year k, with $k \leq t$. In words, this formula allocates an equal share of employment at newly born establishments across all vacancies in that location. For plants that are uniquely located, $v_{p,k} = 1$ and thus we simply sum employment across any new plant born at the location. Similarly, if a plant is not uniquely located but no other establishments at the same address die within five years of the bankruptcy, $v_{p,k} = 1$ for all k. However, if other plants besides the bankrupt plant close in the same location, we allocate an even portion of employment to each vacancy at the location. For example, if 3 establishments (one of which was bankrupt) have closed in a given location when a single new plant is born in the location, we allocate 1/3rd of the employment of the new plant to the bankrupt plant. Note, however, that if in the next year $v_{p,t}$ increases to 4, we continue to allocate 1/3rd of employment to the bankrupt plant, since the new plant could not have taken the spot of this new vacancy. We allocate payroll using exactly the same method.

We allocate employment and wages in this way because when a new plant is born and there are multiple vacancies at its location we cannot determine if the new plant is using the location vacated by the bankrupt plant or that of one of the other co-located plants. There are two main underlying assumptions to the formula. First, that when there are multiple vacancies in a location there is an equal probability that a new plant will occupy any of the vacant units. Hence, when there are 3 vacancies we allocate 1/3rd of the employment to the bankrupt plant on the assumption that there is a one in three chance that the new plant filled the bankrupt establishment's slot.

The second assumption is that $v_{p,k}$ captures all vacancies at an address. Recall that we measure $v_{p,k}$

based on plants appearing in the LBD in the year prior to a bankrupt plant's death. If there are no vacant units at a location prior to the bankrupt plant's death, then $v_{p,k}$ should accurately reflect the total number of plants that have closed at that location in a given year. However, it is likely some locations had vacancies in the year before the death of the bankrupt plant; these vacancies go undetected in our algorithm, and hence $v_{p,k}$ is too low for these cases. This will tend to bias $TotalEmp_{p,t}$ upwards. However, this will only bias our regression estimates if $TotalEmp_{p,t}$ is biased upwards specifically for Ch. 11 or Ch. 7 cases, which seems unlikely. To confirm this, we construct an alternative measure as a simple average of employment across all matches:

$$TotalEmpAlt_{p,t} = \frac{\sum_j emp_{j,p,t}}{n_{p,t}}$$

where $n_{p,t}$ is the total number of new plants that have matched to bankrupt plant p in year t. This alternative formula biases $TotalEmpAlt_{p,t}$ downwards by implicitly assuming that only one plant can fill each vacancy. Results using this alternative specification are essentially identical to our main specification, and so we conclude that the potential bias in $TotalEmp_{p,t}$ does not affect our conclusions.

References

Davis, Steven J, John Haltiwanger, Kyle Handley, Ron Jarmin, Josh Lerner, and Javier Miranda, "Private equity, jobs, and productivity," *The American Economic Review*, 2014, *104* (12), 3956–3990.

Diamond, Peter A, "Aggregate demand management in search equilibrium," *The Journal of Political Economy*, 1982, pp. 881–894.

Dobbie, Will and Jae Song, "Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection," *American Economic Review*, 2015, *105*, 1272–1311.

Foster, Lucia, John C Haltiwanger, and Cornell John Krizan, "Aggregate productivity growth. Lessons from microeconomic evidence," in "New developments in productivity analysis," University of Chicago Press, 2001, pp. 303–372.

Gavazza, Alessandro, "The role of trading frictions in real asset markets," *The American Economic Review*, 2011, *101* (4), 1106–1143.

Gyourko, Joseph, Albert Saiz, and Anita Summers, "A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index," *Urban Studies*, 2008, *45* (3), 693–729.

Mortensen, Dale and Randall Wright, "Competitive pricing and efficiency in search equilibrium," *International Economic Review*, 2002, *43* (1), 1–20.

Petersen, Mitchell A and Raghuram G Rajan, "The benefits of lending relationships: Evidence from small business data," *The Journal of Finance*, 1994, *49* (1), 3–37.

Rubinstein, Ariel and Asher Wolinsky, "Equilibrium in a market with sequential bargaining," *Econometrica*, 1985, pp. 1133–1150.

Wasi, Nada and Aaron Flaaen, "Record Linkage using STATA: Pre-processing, Linking and Reviewing Utilities," Technical Report, Working paper, University of Michigan 2014.